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Asymmetric knowledge transfer in R&D alliances

Martin C. Goossen
HEC Paris
Department of Strategy
martin.goossen@hec.edu

Philip T.J. Bradonjic
Vienna University of Economics and Business
Institute for Entrepreneurship and Innovation
philip.bradonjic@wu.ac.at

Abstract

This study examines the influence of firm and partnership characteristics on asymmetric knowledge transfer in R&D alliances ? the situation of imbalanced interorganizational learning in interfirm partnerships. Past literature on interfirm learning has either discussed cumulative knowledge flows in alliances, while ignoring their potential uneven distribution, or considered factors improving knowledge inflows while overlooking their effects on outflows. Yet, we argue that alliance partners are more concerned about the ratio of knowledge inflows to outflows. Perceiving an R&D alliance as a simultaneous collaboration and learning competition, managers aim to maximize inflows while minimizing outflows. We argue that differences in firm characteristics, technological resources, and alliance experience between two alliance partners influence one?s capability to learn more from its partner firm than vice versa. In addition, these effects will be stronger if an alliance involves the creation of a joint venture. We test our hypotheses on a dataset of 989 R&D alliances formed by North-American manufacturing firms between 1985 and 2000. The results indicate that a higher technological diversity and more slack resources increase net learning benefits while a larger relative firm size has an opposite effect. However, this effect reverses when an alliance is structured as a joint venture.

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RISKS AND OPPORTUNITIES IN INTERFIRM COLLABORATION:

ASYMMETRIC KNOWLEDGE TRANSFER IN R&D ALLIANCES

ABSTRACT

This study examines the influence of firm and partnership characteristics on asymmetric knowledge transfer in R&D alliances – the situation of imbalanced interorganizational learning in interfirm partnerships. Past literature on interfirm learning has either discussed cumulative knowledge flows in alliances, while ignoring their potential uneven distribution, or considered factors improving knowledge inflows while overlooking their effects on outflows. Yet, we argue that alliance partners are more concerned about the ratio of knowledge inflows to outflows. Perceiving an R&D alliance as a simultaneous collaboration and learning competition, managers aim to maximize inflows while minimizing outflows. We argue that differences in firm characteristics, technological resources, and alliance experience between two alliance partners influence one's capability to learn more from its partner firm than vice versa. In addition, these effects will be stronger if an alliance involves the creation of a joint venture. We test our hypotheses on a dataset of 989 R&D alliances formed by North-American manufacturing firms between 1985 and 2000. The results indicate that a higher technological diversity and more slack resources increase net learning benefits while a larger relative firm size has an opposite effect. However, this effect reverses when an alliance is structured as a joint venture.

Key words: R&D alliances, learning race, knowledge transfer

INTRODUCTION

This study investigates the determinants of asymmetric knowledge transfer in R&D alliances. While there is a substantial amount of research looking into antecedents of knowledge transfer in interfirm R&D arrangements (e.g. Chen, 2004; Inkpen & Tsang, 2005; Van Wijk et al., 2008), little attention has been paid to which factors simultaneously improve knowledge inflows while constraining knowledge outflows (Lavie, 2006). This study identifies firm-level and alliance-level factors that are related to uneven knowledge transfer. By doing so, we contribute to the literature on antecedents of asymmetric knowledge transfer in R&D alliances (Kale & Singh, 2007). Secondly, we also add to the literature on competition and learning races in interorganizational collaboration (Gulati & Singh, 1998; Hamel, 1991; Lavie, 2007).

A large amount of literature has explored organizational arrangements for firms to share knowledge and resources to pursue a common goal (Das & Teng, 2000). In addition to that objective, R&D alliances are means for firms to share and transfer proprietary knowledge, skills and expertise (Oxley & Sampson, 2004). As a result, organizations involved in R&D alliances increase their learning and innovative performance. Several studies have examined the factors that facilitate or inhibit effective and efficient knowledge transfer in R&D alliances (for a review, see Easterby-Smith et al., 2008). Seminal work on this topic by Mowery et al. (1996) has shown that the form of arrangements and the industry positions vis-a-vis each other significantly influence knowledge transfer in their collaboration. In a meta-analysis of over seventy empirical studies, Van Wijk et al. (2008) found that characteristics of knowledge itself, the organizations involved, and the network influence knowledge transfer in interorganizational collaborations.

This research, however, has largely overlooked the competitive elements of knowledge transfer in R&D alliances. In such a competitive perspective, one needs to weigh the benefits of

an R&D alliance (knowledge inflows from the partner firm) against the costs of such collaboration (knowledge outflows towards the partner firm). While firms establish a partnership to pursue a commonly agreed objective, there will also be unintended sharing of knowledge, expertise and resources (Lavie, 2006). Such unintended spillovers provide concurrently opportunities and risks for innovation, which ultimately lead to competitive advantages and threats (Kale et al., 2000). As a result, Khanna et al. (1998) modeled R&D alliances as learning races among collaborating partners. The current literature has neglected three major aspects of such a conceptualization.

First, most research has only considered the total amount of knowledge transferred between R&D partners; not the ratio of inflows versus outflows. These studies have mainly identified factors that foster overall knowledge transfer, ignoring the direction of these knowledge flows and their potential imbalance. For instance, literature on the strength, intensity and duration of collaboration (e.g. Tsai & Ghoshal, 1998) concluded that these factors all positively contribute to knowledge sharing and innovation. However, these factors can stimulate knowledge flows in either direction: both inflows and outflows. Similarly, studies on licensing agreements have shown how contract clauses stimulate or hamper knowledge acquisition and re-use (e.g. Leone & Reichstein, 2012). However, knowledge transfer in such cases tends to be majorly one-directional.

Second, many studies have ignored that factors facilitating knowledge inflows may equally assist knowledge outflows. For instance, several studies have concluded that firms with a stronger absorptive capacity are more effective in absorbing the partner firm's knowledge and skills (Lane & Lubatkin, 1998). Whereas these studies, in line with our perspective, take a firm-level perspective to alliances, they still ignore the fact that such characteristics may also ease

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knowledge outflow. Similarly, studies on diversity have shown how technologically different alliance partners contribute to the focal firm's interfirm learning (Nooteboom et al., 2007), ignoring the fact that such a strategy provides exactly equal benefits to alliance partners.

Thirdly, firms probably select into alliances where benefits, including knowledge transfer, are shared equally or jointly among partners (Li et al., 2008). First, firms rich in knowledge and resources have little incentive to enter interorganizational research collaborations (Ahuja, 2000b). So while firms rich in knowledge and expertise are attractive alliance partners, their needs to collaborate are less. Second, firms looking for alliance partners are part of an assortative matching process. Partner selection involves aspects that enable knowledge transfer (Li et al., 2008), but may also involve aspects that result in (more) asymmetric learning. Managers may evaluate alliance partners and already incorporate the likelihood of asymmetric knowledge transfer. As such, alliances are only realized when the expected benefits of collaborating plus inbound knowledge spillover exceed the expected costs of collaborating plus outbound knowledge spillovers. These issues need to be properly addressed when investigating uneven knowledge transfer in R&D alliances.

In this study, we identify firm-level and alliance-level factors that cause asymmetric knowledge transfer in alliances designed for joint research and development. In addition, we assess how alliance structure can strengthen and weaken these imbalances. In a large-scale sample of 989 R&D alliances formed between 1985 and 2000, we find strong results for asymmetric knowledge transfer. The amount of slack resources in an alliance firm relative to that of its partner firm increases its interorganizational learning rate, i.e. the focal firm will learn more from its partner than vice versa. Relative absorptive capacity, measured via technological diversity, has a similar effect on interfirm learning. The size of a firm, however, has an opposing

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effect: smaller firms learn more by participating in R&D alliances. This effect for firm size reverses when alliances are structured as joint venture.

This study contributes to the literature on knowledge transfer and learning races. By identifying factors that lead to asymmetric knowledge transfer, this study increases our understanding of competition in R&D alliances and joint ventures. While previous studies examined elements that assist knowledge transfer in either direction or firm characteristics that aid knowledge inflows, less is known about the imbalance of knowledge transfer. Surprisingly, factors that enhance knowledge inflows can also increase knowledge outflows. For example, alliance experience increases knowledge inflows (Rothaermel & Deeds, 2006), but we do not find that this result is asymmetrical, meaning that the knowledge outflows also increase. This may change the favorable views on absorptive capacity and alliance experience for interfirm learning. Whereas these capabilities definitely help in capturing external knowledge, they equivalently support knowledge outflows. Unless firms also have additional capabilities to exploit knowledge more effectively, there is little opportunity for competitive advantage.

In addition, findings of this study reframe the debate of knowledge transfer and interfirm learning by clearly including a competitive element. Building on the idea of learning races in R&D partnerships (Hamel, 1991), we argue that alliances include both collaboration and competition. From a firm's point of view, successful knowledge transfer in alliances should therefore no longer be measured via accumulated knowledge transfer or knowledge inflows, but via knowledge transfer asymmetries. This unevenness directly determines to what extent R&D collaboration can provide competitive advantages or pose strategic threats. This is an important issue for managerial theory as well as practice.

Prior Literature on Knowledge Transfer in R&D Alliances

An abundant literature has discussed the importance of R&D alliances in

interorganizational learning and knowledge transfer (Chen, 2004; Easterby-Smith et al., 2008).

Initially, R&D collaborations are formed to either jointly explore new fields of technology, or to

exploit complementary knowledge, resources, and skills (Inkpen, 2000). This increases,

consistently and evenly, the innovativeness and performance of all partners involved an

interorganizational partnership (Sampson, 2007). The degree of learning and knowledge transfer

in this case depends on seven major factors. First, the rationale of an alliance creates an

opportunity-ability tradeoff. If R&D alliances are formed to leverage similar knowledge and

technologies, there is limited opportunity for learning. On the contrary, if firms partner to exploit

complementary knowledge, there are substantial learning opportunities. However, such

differences also cause difficulties in sharing knowledge because firms lack a common

understanding (Dussauge et al., 2000; Lavie, 2006). Second, the purpose of an alliance regulates

the type of knowledge and technologies involved, which guides partners' learning opportunities

(Oxley & Sampson, 2004). Interorganizational learning is faster and easier if knowledge and

technologies shared among partners are explicit and straightforward, while tacit and ambiguous

information hampers learning (Hansen, 1999; Simonin, 1999). Third, the alliance agreement also

determines the amount of time and resources partners should dedicate to their collaboration.

Human capital is particularly important for interfirm knowledge transfer: learning increases if

R&D alliances involve more employees, all communicating and collaborating and intensively.

Fourth, the structure of an alliance has a profound effect on knowledge transfer and information

exchange. For example, Sampson (2007) argues that knowledge transfer and innovation is easier

when alliances are structured joint ventures. Such new entities overcome bureaucratic hurdles for information exchange in contractual arrangements. Knowledge sharing also increases if alliances involve colocation of employees from both firms: this fosters communication and collaboration among employees of both firms (Singh, 2007). Fifthly, the presence of social capital and trust among alliance partners is an important facilitator of knowledge transfer in alliances (Inkpen & Tsang, 2005). The belief that a partner firm will behave honestly increases a firm's willingness to share knowledge and information. Sixth, technological differences increase learning opportunities but limit learning abilities of both organizations (Nooteboom et al., 2007). Finally, a range of environmental characteristics (cultural distance, transparency, institutional environment, etc.) influence learning opportunity and ability of R&D alliances. Regarding this literature, it is important to note that it considers the overall, cumulative degree of learning and knowledge transfer among all alliance partners.

A second line of literature has looked how firms benefit differently from similar alliances by identifying firm characteristics that increase knowledge inflows from R&D alliances. In this view, R&D alliances provide a window of opportunity to learn knowledge and knowhow residing in partner firms. Factors related to unilateral knowledge flows generally fall into four groups. First, firm structural characteristics facilitate the absorption and utilization of partner firm knowledge and information (Van Wijk et al., 2008). The size and structure of an organization influence a firm's learning capability. For instance, decentralized firms are more flexible and less bureaucratic which increases business units' willingness to share and learn information from partners (Gupta & Govindarajan, 2000). Second, a firm's absorptive capacity is an important capability for learning in R&D alliances (Zahra & George, 2002). According to the absorptive capacity literature, firms develop mechanisms and routines to recognize, assimilate

and apply external information (Cohen & Levinthal, 1990). As such, firms with high absorptive capacity face a direct increase of knowledge inflows when new alliances are created (Chen, 2004). Third, various studies have shown the importance of prior alliance experience (Hoang & Rothaermel, 2005). During alliances, firms develop capabilities, insights and routines for managing interfirm projects. This increases the efficiency and success of future alliances (Heimeriks & Duysters, 2007). In addition, it also increases knowledge absorption and exploitation from alliance partners (Rothaermel & Deeds, 2006). Fourthly, the benefit a firm obtains from one alliance may depend on other alliances that this firm is involved in. In a review article, Wassmer (2010) discussed how firms develop a strategy and management approach for each alliance based on their entire portfolio. The motivation to learn from one alliance partner then depends on the importance, relevance and uniqueness of that partner's knowledge. Regarding this literature, it is important to notice that it looks at the influence of knowledge inflows for a focal firm without regard for knowledge outflows towards its alliance partners.

Competing while Collaborating

To introduce the element of competition present within R&D alliances, we build upon two related theoretical concepts present in the literature on cooperative strategies: the value creation versus appropriation discussion and the so-called learning race idea. Literature on cooperative strategies has extensively discussed the difference between value creation and value appropriation in any type of collaboration (Lepak et al., 2007). According to this literature, collaboration among multiple parties increases their overall value via a "the whole is greater than the sum of its parts" logic. If there were no superadditive effect of collaborating, cooperation would not occur in the first place. Subsequently, newly created value is distributed among parties

involved in the collaboration (Lavie, 2007). While previous management literature assumed equal share of benefits, this literature argues that value is hardly ever distributed evenly. Instead, during their collaboration, parties are actively involved in a competition to increase their share of benefits (Khanna et al., 1998).

Such a view is particularly appropriate with regard to R&D alliances. In R&D alliances, firms exploit complementary knowledge, aim to share risks in exploring new technologies, or develop a new product together. Therefore, they have a clear aim for creating joint value. Firms also employ various strategies to appropriate value from R&D alliances. Some of these are hard to contractually specify or prove legally, creating a threat of opportunistic behavior (Ahuja, 2000a). Lavie (2006) provides us a conceptual framework to analyze the costs and benefits of learning in R&D alliances. First, intended knowledge spillovers occur when firms collaborate. In exploration alliances, this means both firms gain access to new technological knowhow. In exploitation alliances, this means both firms gain access to its partner's complementary knowledge. While the opportunities here are either equal or known ex ante, firms may still vary in their abilities to absorb and apply new knowledge in their own products and processes. Second, R&D alliances often involve unintended spillovers (Singh, 2007). These knowledge outflows towards its partner are not foreseen nor intended by the firm. While unintended knowledge spillovers are beneficial to the receiving alliance partner, the loss of proprietary knowledge may form a direct competitive threat to the disclosing firm. The overall value created in the alliance is therefore not simply the intended development or exchange of knowhow, but also relative benefits and costs of unintended spillovers. In short, the value an individual alliance partner obtains is the value of intended knowledge spillovers plus the value of unintended knowledge inflows minus the costs related to unintended knowledge outflows.

In a similar vein, some studies have conceptualized alliances as learning races. Hamel (1991) describes how managers see R&D alliances mainly as opportunities to learn new capabilities or technologies. Their (mostly undisclosed) learning objectives have a strong impact on how they manage interorganizational collaborations. First, these objectives may diverge from the official purpose as stated in the alliance agreement. This forms a breeding ground for tension and conflict among alliance partners. Second, such managers will often spend large amount of resources and attention to the alliance while absorbing new knowledge and information, but starkly reduce it after a firm has obtained the knowhow it was going after. Larsson et al. (1998) even pose this as a dilemma arguing that a "good partner" will inevitably become a victim of opportunistic behavior by other firms while predatory behavior by all partners eliminates any value creation within the alliance. However, Khanna et al. (1998) show how one firm can tactically use resource allocation to regain balance in interorganizational learning when its partner has taken the lead in the learning race.

While learning races provide a very stylized view on asymmetric knowledge transfer in alliances, it provides us with a number of additional insights. First, it reveals that imbalanced learning can occur even for intended knowledge spillovers. If firms learn at different rates, the faster learning firm has a lower incentive to collaborate as soon as it absorbed all potential spillovers. This poses a threat to the partner firm. Second, learning races have shown which tools alliance partners can use to either take a lead in the race or to regain balanced knowledge transfer. We know focus on firm and alliance factors that lead to such asymmetric knowledge transfer.

Antecedents of Asymmetric Knowledge Transfer

Firm characteristics. Firm structure, strategy and experience are important determinants for their ability to learn and innovate (Damanpour, 1991). These factors help an organization in developing capabilities for absorbing and applying relevant external knowledge (Cohen & Levinthal, 1990). Simultaneously, these factors also help in developing capabilities for protecting proprietary knowhow and reducing knowledge outflows. Therefore, differences in structure and strategy among alliance partners may explain asymmetric or imbalanced knowledge transfer in R&D alliances.

First, a difference in firm size of alliance partners is likely to influence their ability to absorb knowledge since size is a major predictor of firm innovation. Past research on the role of firm size in interorganizational collaboration has shown ambiguous results (Van Wijk et al., 2008). On the one hand, larger firms have more resources available to invest in an R&D alliance, which increases their learning and value appropriation. Smaller firms with minimal means cannot invest the same amount of time and effort to learn and absorb its partner's proprietary knowledge. On the other hand, while larger firms have more opportunities to enter into partnerships, their motivation to do so is reduced (Ahuja, 2000b). They tend to be become more inward focused, become less active in search external knowhow and less likely to adopt it (Katz & Allen, 1982). From the outset, it is unclear which line of argumentation dominates though both seem equally valid. For that reason we propose this dual hypothesis:

H1a: firm size of alliance partner i relative to j increases asymmetric knowledge transfer towards firm i and vice versa.

H1b: firm size of alliance partner i relative to j increases asymmetric knowledge transfer towards firm j and vice versa.

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Note that asymmetric knowledge transfer here means the differences in value captured (knowledge inflows minus outflows) by each alliance partner. We expect the effects to be symmetric, meaning that if firm i is larger than firm j, it will capture more (H1a) or less (H1b) value, but if firm i is smaller than firm j, it will capture less (H1a) or more (H1b) value than firm j from the R&D alliance.

Second, the presence of slack resources in an organization has often been related to its innovative performance (Nohria & Gulati, 1996). Slack resources means the presence of financial and human capital in excess of those absolutely needed to continue current operations. Slack resources allow an organization to experiment with new techniques and technologies, thereby nurturing serendipitous innovation. Once firms enter into alliances, the presence of slack resources enable organizations to acquire missing capabilities from its alliance partner (Patzelt et al., 2008). Managers can direct slack resources towards the alliance in order to perform activities that will give it a lead in the learning race. In addition, slack resources can be used to immediately exploit newly absorbed knowledge. This increases an organization's value appropriation of an R&D alliance. On the contrary, efficient organizations with little excess resources can fulfill their part of the alliance but will miss out on the learning opportunities it provides. First, they have less time and effort to spend on obtaining unintended knowledge spillovers. Second, they have less time and effort to spend on fully exploiting newly obtained knowledge. As a result, we suggest that differences in slack resources between two alliance partners leads to asymmetric knowledge transfer in favor of the firm with more slack resources:

> H2: slack resources of alliance partner i relative to j increases asymmetric knowledge transfer towards firm i and vice versa.

Third, firm innovation is inherently linked to its R&D intensity, i.e. the share of its resources dedicated to R&D activities (Cohen et al., 1987). To start, R&D intensity indicates the

financial resources R&D departments have at their disposal for developing new technologies, products and processes. Munificent resources allow R&D departments to develop new technologies while simultaneously improving existing ones, whereas scarcity forces managers to choose among these options (Gupta et al., 2006). Moreover, R&D intensity signals dedication to R&D by a firm's top management. By diverging resources from other activities (marketing, manufacturing, etc.) to R&D, the management reveals its intention to learn and innovate. Finally, R&D intensity may be part of the firm's overall business strategy with firms pursuing an aggressive competitive strategy dedicating more time and resources on new product development (Miles et al., 1987).

Yet, the role of R&D intensity in alliances remains unclear since Mowery et al. (1996) found no effect of R&D intensity on combined knowledge transfer (e.g. the sum of all knowledge flows). Nevertheless, R&D intensity may still influence the value appropriation part of R&D alliances. First, R&D intensity proxies a firm's R&D experience and as such its routines and capabilities to acquire and exploit new knowledge. Second, this experience in combination with an aggressive business strategy also limits unintended spillovers of valuable knowledge towards its alliance partner. Therefore we expect that differences in R&D intensity among alliance partners result in asymmetric learning:

> H3: the R&D intensity of alliance partner i relative to j increases asymmetric knowledge transfer towards firm i and vice versa.

Fourth, a firm's ability is largely determined by its technological diversity. First, according to recombinant search literature (e.g. Fleming, 2001), most innovation is the recombination of existing technologies in new ways or the combination of previously unconnected technologies. Technological diversity provides more opportunities for potential recombination, hence it increases firm innovation. Second, absorptive capacity literature has shown that technological

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diversity reflects the diversity of knowledge and knowhow within an organization. Such diversity enables a firm to absorb new external knowledge (Lance & Lubatkin, 1998). This is because it is much easier for firms and employees to learn and assimilate external knowledge when it is related to its current knowledge base (Cohen & Levinthal, 1990).

Absorptive capacity and technological diversity play a major role in R&D alliances (Zahra & George, 2002). Absorptive capacity allows a firm to understand its partner's knowledge even when it is different from its own expertise. Therefore, technological diversity increases the firm's ability to learn from its alliance partner. In addition, absorptive capacity also indicates a firm's ability to apply and exploit external knowledge in new project outside the scope of the alliance (Lance & Lubatkin, 1998). Technological diversity also increases the number of recombinant opportunities for newly acquired knowledge and knowhow. Firms with high technological diversity and absorptive capacity thus have an increased motivation, opportunity and ability to learn from R&D alliances. All these arguments are only related to knowledge inflows and do not seem to promote knowledge outflows. Therefore we hypothesize:

> H4: technological diversity of alliance partner i relative to j increases asymmetric knowledge transfer towards firm i and vice versa.

Fifth, organizations build an alliance management capability via their past experiences in interorganizational partnerships. Alliance experience improves an organization's capability to manage future alliances via a process of accumulating, codifying and diffusing experiences and knowhow from prior and current alliances (Kale & Singh, 2009). Rothaermel and Deeds (2006), for example, have shown that a venture with more alliance experience increases its ability to perform many alliances simultaneously while still obtaining benefits for new product development. In addition to knowledge inflows, prior alliance experience may have taught a firm how to protect its proprietary knowledge and intellectual property rights by avoiding outflows

(Kale et al., 2000). Therefore, we argue that differences in alliance experience among alliance partners will lead to asymmetric knowledge transfer in favor of the most experienced firm:

> H5: alliance experience of alliance partner i relative to j increases asymmetric knowledge transfer towards firm i and vice versa.

Alliance characteristics. Besides the characteristics of partner firms, alliance characteristics themselves can also influence asymmetric learning. Here, we focus on two elements: the scope of an R&D alliance and the structural arrangement of R&D alliances.

First, R&D alliances revolve around the partners' shared objective (Oxley & Sampson, 2004). The goal and scope of an alliance – whether the development of a drug, integrating existing software into a new package, or finding new uses for a particular type of semiconductor – are clearly stated in the alliance agreement. While complementary resources are often the rationale of R&D alliances, it is not uncommon that the scope of an alliance is more closely related to either one of the alliance partners. For instance, R&D alliances between biotech ventures and pharmaceutical firms almost exclusively focused on biotech and little on chemical compound development.

The relatedness of the field and scope of an alliance may influence a firm's ability and opportunity to learn from its partner in opposing ways. Initially, the opportunities to access and learn novel knowledge and information are larger when the alliance focuses on unfamiliar fields. For example, Nooteboom et al. (2007) have shown that partnerships with technologically different organizations provide larger learning opportunities. This, however, is only true if the alliance is (at least partially) focused on the partner's technology. Subsequently, the ability to learn from a partner firm may reduce if the alliance focuses on distant fields. The lack of related knowledge may inhibit an organization's learning process (Cohen & Levinthal, 1990). Finally, the motivation of a firm to explore new fields may vary. On the one hand, it provides new

opportunities for an organization. On the other hand, it makes learning harder and may distract a firm from developing its core capabilities. Therefore we propose a dual hypothesis:

> H6a: relatedness of an alliance to firm i relative to firm j increases asymmetric knowledge transfer towards firm i and vice versa

> H6b: relatedness of an alliance to firm i relative to firm j increases asymmetric knowledge transfer towards firm j and vice versa

Finally, the structural arrangement of an alliance influences knowledge transfer and interorganizational learning (Van Wijk et al., 2008). Alliances are either structured as contractual arrangements between two independent firms or via the creation of a new legal entity (a joint venture) of which the equity is held equally by both organizations. Empirical studies on this topic have overwhelmingly shown how joint ventures are superior arrangements for interfirm knowledge transfer (e.g. Mowery et al. 1996). Joint ventures involve more frequent communication and more intensive collaboration among alliance partners. This creates the strong ties among individuals that are necessary for the transfer of complex, tacit knowledge (Hansen, 1999). In social capital research (Tsai & Ghoshal, 1998), tie strength has been related to trust and willingness to share knowledge and resources. Joint venture arrangements involve a larger dedication of resources and assets, so they signal strong ties and trust among alliance partners.

Though the structural arrangement of an alliance influences overall knowledge flows among partners, it influences inflows and outflows symmetrically. Compared to contractual arrangements, joint ventures increase inflows of intended and unintended knowledge spillovers but simultaneously also outflows. However, the structural arrangement may moderate the effects of firm structure, firm strategy and alliance scope characteristics on asymmetric knowledge transfer in R&D alliances. Since joint venture arrangements increase overall knowledge flows in R&D alliances, it will also increase the asymmetry of knowledge flows among alliance partners.

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Therefore, we hypothesize that the earlier hypothesized relationships are stronger in case of joint ventures:

> H7: the relationships of hypotheses 1 to 6 are positively moderated, i.e. strengthened, if R&D alliances are structures as a joint venture.

METHODOLOGY

Sample Selection and Data Collection

We test our hypotheses on a sample of R&D alliances created by North-American manufacturing firms during 1985 and 2000. These criteria are applied for a number of reasons. While single-industry studies allow for more precision, it inherently reduces the generalizability of their findings. Since our aim is to contribute to alliance research in general, we focus on all industries where such collaborations are common. The manufacturing industries (SICs 3000-4999) heavily rely upon tacit knowledge and expertise for its products and process innovation. A quick analysis of major databases indicates that a substantial part of all R&D alliances are formed by manufacturing firms. In addition, many past studies on interfirm R&D collaboration have used (subsamples of) this setting for their empirical analysis (e.g Ahuja, 2000a; Cohen & Levinthal, 1990; Dussauge et al., 2000).

Within these industries, we restrict ourselves to (i) only North-American alliances (ii) of up to five partners (iii) formed by public North-American firms (iv) between 1985 and 2000 to overcome issues regarding data availability and comparability. We limited our sample to public firms to ensure organizational and financial data are available. The number of partners in an alliance was limited to five to exclude larger consortia that often pursue non-R&D purposes. Since we use patent characteristics as proxies for learning, we limited our sample to North America to be sure all parties would seek intellectual property protection from the USPTO.

We explicitly focus on alliances that involve bilateral R&D collaboration, i.e. that involve joint knowledge creation or mutual knowledge exchange. With the take-off of markets for technology, there has been a rising number of licensing agreements. Such agreements, however, are intended to pursue one-directional knowledge transfer. Therefore, pure licensing agreements are eliminated from our sample. Instead, only alliances that involve some joint R&D are included (e.g. cross-licensing, joint R&D, or cross-technology transfer). These alliances may contain licensing agreements in order to give all parties access to certain proprietary technology, but are intended to go beyond that.

The sample of this study was created by combining three data sources. We started by drawing our sample of R&D alliances from the SDC Platinum alliance database. While fully aware of the shortcomings of any alliance database, "results suggest ... that the alliance databases are a valuable, and generally reliable ... resource for the study of interorganizational relationships" (Schilling, 2009:259). The sample of R&D alliances is then complemented with partner firm organizational and financial data collected from WRDS Compustat. We relied on SEC Edgar archives to overcome issues regarding multiple listings and name changes. Finally, patent data from the NBER U.S. Patent Citations Data File are added (Hall et al., 2001).

The creation of the dataset slightly suffered from incomplete data, thereby marginally reducing the number of observations. Using the criteria for the alliance and alliance partners, an initial screening of the SDC Platinum alliance database provided 891 alliances involving 759 different firms. Since we look at knowledge transfer asymmetries, alliances are structured as dyads. For multipartner alliances, each unique dyad among partners is included in our sample as long both partners are public North-American manufacturing firms. For each of these firms, we added financial and organizational data from WRDS Compustat and patent data from the NBER.

In case, we could not obtain full data for either one of the partners, the dyad was eliminated from the dataset. The final sample consists of 824 alliances with 686 unique partner firms involved in 989 dyads.

Dependent Variable: Knowledge Transfer Asymmetry

Knowledge transfer asymmetry is the imbalance in knowledge transferred – i.e. inflows minus outflows – between alliance partners. Knowledge transfer is a largely unobservable, interpersonal process that involves intensive communication and socialization (Simonin, 1999). Therefore, we rely upon proxies to measure the extent by which knowledge flows between partners. Mowery et al. (1996) carefully developed patent cross-citation rates as a method for examining interorganizational knowledge flows. Despite recent criticism on the use of patent citations (e.g. Alcacer & Gittelman, 2006), they still provide a robust proxy for interfirm learning. We adapted the measure of Mowery et al. (1996) to capture knowledge transfer asymmetry as follows:

$$Knowledge\ transfer\ asymmetry_{i,j,t} = \left(\frac{X_{i \rightarrow j}^{t0,t4}}{X_i^{t0,t4}} - \frac{X_{j \rightarrow i}^{t0,t4}}{X_j^{t0,t4}} \right) \times 100$$

with X_i and X_j the total number of citations made on patent successfully applied during a five-year period starting from the year of alliance formation, and $X_{i \rightarrow j}$ and $X_{j \rightarrow i}$ being the number of citations from firm i to firm j and vice versa. Cross-citations are a very small portion of all citations, so we multiplied it by 100 to gain more comprehensible regression coefficients[1].

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[1] Note: this does not change the significance of coefficients, but only reduces the number of decimals

Independent variables

Relative size. Relative firm size is calculated as $\ln(Assets_i) - \ln(Assets_j)$. Firm assets are preferred over firm sales since few firms in our sample report close to zero sales in particular years. By taking the natural log of a firm's assets, we ensure that the differences are relative to the partners' original sizes. For validity, we also computed the measure using sales data and found a correlation of 0.98 which reduces our concerns by using assets instead of sales.

Relative slack resources. Slack resources are resources the firm possesses in excess of what is absolutely necessary for current operations (Nohria & Gulati, 1998). We proxy slack resources by financial munificence as expressed in its current ratio (current assets ÷ current liabilities). For both firms, we first calculated the current ratio and winsorized it at a level of five to cap extreme values. Relative slack resources is then computed as firm i's current ratio minus firm j's current ratio.

Relative R&D intensity. R&D intensity indicates a firm's resource allocation toward R&D activities (Cohen et al., 1987). First, we calculated the R&D intensity (R&D expenses ÷ sales) for both firms and capped at a value of one since some firms report R&D expenditures exceeding their annual sales. Relative R&D intensity is then computed as firm i's R&D intensity minus firm j's R&D intensity.

Relative technological diversity. The technological diversity of a firm indicates its diversity in knowledge, skills and capabilities. Diversity in knowledge and skills helps an organization to learn new external information as well as turning it into useful practices (Cohen & Levinthal, 1990). We use the following formula to measure differences in diversity:

$$Relative\ technological\ diversity_{i,j,t} = \left(1 - \sum_k^K \left(\frac{X_{i,k}^{t-5,t-1}}{X_i^{t-5,t-1}}\right)^2\right) - \left(1 - \sum_t^T \left(\frac{X_{j,k}^{t-5,t-1}}{X_j^{t-5,t-1}}\right)^2\right)$$

This is the Blau's index of firm i's patent diversity over technological classes (in the five years before alliance formation) minus firm j's Blau's index. Since both variables range between 0 (low diversity) and 1 (high diversity), the final variable ranges between -1 and 1.

Relative alliance experience. Experience in alliance formation and execution increases a firm's insights and develops best practices for alliance management (Hoang & Rothaermel, 2005). Therefore, we counted all alliances established by each partner over a ten-year period before the focal alliance. We then measured relative alliance experience as follows:

$$Relative\ alliance\ experience_{i,j,t} = \frac{\left(\#\ alliances_i^{t-10,t-1} - \#\ alliances_j^{t-10,t-1}\right)}{\left(\#\ alliances_i^{t-10,t-1} + \#\ alliances_j^{t-10,t-1}\right)}$$

This measure ranges between -1 and 1 and prevents the extreme values that a simple subtraction would lead to. For validity, we also computed this variable using a five-year window and using only R&D alliances: all four measures have correlations larger than 0.9.

Relative alliance industry relatedness. For this variable, we first measure each firm's relatedness to the alliance by counting the number of overlapping subsequent digits between the alliance's SIC and a firm's primary SIC (e.g. 3661 and 3647 have the first two digits in common, 3113 and 3413 only the first digit). Relative alliance industry relatedness is computed as firm i's relatedness minus firm j's relatedness, resulting in an integer measure ranging from -4 to 4.

Joint venture. In the last hypothesis, we argue that alliances structured as joint ventures increases asymmetric knowledge transfer since they generally increase cumulative knowledge flows (Mowery et al., 1996). So, we add a dummy variable indicating if the alliance is structured as a joint-venture agreement.

Control Variables

To exclude alternative explanations or drivers for observed asymmetry, a number of control variables are added to the regression. The controls are related to alliance characteristics, the partner's dyadic characteristics, and to general patent citations patterns.

Licensing agreements. Some alliances revolve around developing or exploiting patented technologies, which are usually shared between firms via licensing agreements. This is likely to increase overall knowledge transfer between partner firms (Leone & Reichstein, 2012). So we included a dummy indicating if the alliance agreement involved (cross-)licensing.

Downstream agreements. Many R&D alliances also contain downstream elements related to the commercialization of newly developed or shared technologies, like manufacturing, marketing and distribution (Rothaermel & Deeds, 2004). Thus, we include a dummy equaling one if an alliance agreement contains such elements.

Alliance based in Canada. While the large majority of the alliances in our sample is located in the United States, few are located in Canada. We add a dummy to correct for the potential effect of this on knowledge flows.

Number of alliance partners. Multipartner alliances are inherently different from two-partner alliances in terms of stability and reciprocity (Zeng & Chen, 2003). Though it is not immediately visible how this would increase or reduce asymmetry, the number of alliance partners is added as a control variable.

Prior R&D alliances. Prior alliances have significant effects upon subsequent alliance formation, governance, trust, and performance (Gulati, 1995a). Hence, a dummy variable indicating prior alliances between partners (i.e. alliances that started during five years prior to the

current R&D alliance) has been added. Potential alternative specifications (using a ten-year window, only including R&D alliances, and using a count measure) were highly correlated.

Buyer-supplier relationship. We added a dummy equaling one if the alliance was related to a buyer-supplier relationship, as indicated by SDC Platinum. Such vertical alliances are different from horizontal alliances and involve a lower competitive element since partners are active in different industries. This may reduce IPR concerns and increase knowledge flows.

Spatial distance. Geographical proximity is an important determinant for knowledge diffusion. As such, distance may also influence knowledge exchange in alliances and potentially knowledge transfer asymmetries. We added the distance between headquarters of both partner firms (logged) as a control variable.

Pre-alliance asymmetry. The observed imbalance in knowledge transfer may simply occur because there was already uneven interfirm learning before the alliance is created (Mowery et al., 1996). Therefore pre-alliance knowledge asymmetry is computed similarly to knowledge transfer asymmetry in R&D alliances, but now via citations in patents applied for during a five-year window prior to alliance formation.

Relative technological success. An observed imbalance in transfer asymmetries may also be caused by relative technological success of either one of the partners (Mowery et al., 1996). If firm i develops a successful technology during the alliance period, an increase in number of citations by firm j (as well as all other firms) is expected but unrelated to alliance formation. To control for this effect, a control variable is calculated as follows:

$$Relative\ innovative\ succes = \frac{X_{n \to i}^{t0,t4} / X_{n \to i}^{t-5,t-1}}{X_{n \to j}^{t0,t4} / X_{n \to j}^{t-5,t-1}}$$

with $X_{n \to i}$ being all citations from all firms to patents belonging to i. This is repeated for two five-year periods (before and after alliance formation) for both firms.

Total knowledge transferred. Despite its corrections, asymmetric knowledge transfer may be correlated with the total amount of knowledge transferred. Surely, there will be no asymmetry if there is no knowledge transfer observed after alliance formation. Therefore, the change in total number of cross-citations is added as a control variable:

$$Total\ knowledge\ transferred_{i,j,t} = \ln\left(X_{i \to j}^{t0,t+4} + X_{j \to i}^{t0,t+4}\right) - \ln\left(X_{i \to j}^{t-5,t-1} + X_{j \to i}^{t-5,t-1}\right)$$

Year dummies. The number of alliances, patents and patent citations have increased over time. Thus, year dummies are added to correct for any temporal effect.

Selection Bias

Alliance formation is not a random process (e.g. Gulati, 1995b). Consequently, the sample of observed alliances is not random, but subject to a selection process that involves self-selection into alliances and a two-sided matching process for finding alliance partners. In this case, it would be naive to assume that managers are unaware of potential opportunities and threats rising from asymmetric knowledge transfer. We need then to correct for this selection bias, as it otherwise would lead to flawed findings (Hamilton & Nickerson, 2003). Therefore, we apply a two-stage estimation as proposed by Heckman (1979) and calculate the inverse Mill's ratio to control for this issue.

First, we created a control group by generating all potential dyadic relationships of alliance partners in our sample for a given year.[2] We then excluded all these dyads that actually formed a partnership, as indicated by SDC Platinum (whether R&D or non-R&D, whether in focal year or any other year during 1980 to 2010). This leads to 961 allied and 82,044 non-allied pairs[3].

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[2] For example, if we observe ten unique alliance partners in 1986, there are 10×9×.5=45 potential alliances generated. We do this year-by-year since many firms existing in 1985 no longer exist in 2000.
[3] We observe 989 alliances which involve 961 unique pairs (some firms are involved in multiple alliances).

Second, we identify three variables that can be used as instruments: partners' industrial

relatedness, partners' spatial proximity, and partners' technological similarity. These three

variables are symmetric and may influence overall knowledge transfer, but not asymmetric

knowledge transfer. Industrial relatedness is measured as the number of subsequent overlapping

digits in both firms' primary SIC codes, thereby ranging from 0 to 4. Spatial proximity is the

distance between firms' headquarters (logged)[4]. Technological similarity is based on the overlap

of pre-alliance technological profiles of both partner firms using Jaffe's (1986) index:

$$Technological\ similarity = \frac{\sum_{k=1}^{K} f_{ik}f_{jk}}{\left(\sum_{k}^{K} f_{ik}^2\right)^{1/2} \left(\sum_{k}^{K} f_{jk}^2\right)^{1/2}}$$

We run a probit regression with these three variables and year dummies to generate the

inverse Mill's ratio. For space reasons, this regression table is excluded here, but it shows that all

three instrumental variables have a significant effect on alliance formation. The inverse Mill's

ratio is added as a control variable in the second stage regressions to correct for endogeneity.

Analytical Technique

To improve the causal validity of our analysis, all independent and control variables were

measured in the year(s) preceding alliance formation (unless otherwise indicated). Since the

dependent variable is a continuous variable with a normal distribution, we decided to use

standard ordinary least squares regression. Despite common concerns regarding this method, it

seemed the most appropriate, straightforward method in our case. High VIFs for the inverse

Mill's ratio and some year dummies initially caused some concern, but results remain remarkably

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[4] We use the business addresses from the SDC database and obtain their geographical coordinates from Google Maps, which allows us to calculate their distance in kilometers.

stable when corrected for these (either by removing them from the regression or by using robust standard errors).

RESULTS

The descriptive statistics and correlations of the sample are reported in Table 1. The dependent variable, Asymmetry, has a mean close to zero and a standard deviation of 3.7. This indicates that asymmetry for all alliances is close to zero, but varies significantly among the observations. Many variables have minimum and maximum values caused by their method of computation, but even those who do not (Relative size, Pre-alliance asymmetry, etc.) follow this pattern are still highly symmetric. The descriptives further show that around 16.1% of the alliances involve an equity arrangement, e.g. a joint venture. While most correlations are significant at the 5%-level, all of them remain below |0.8| and are no cause of concern.

INSERT TABLE 1 HERE

Table 2 below reports the results of the regression analysis to test the direct effect of relative differences on knowledge transfer asymmetry, as stated in the first six hypotheses. Model 1 only includes the control variables. Pre-alliance asymmetry as well as relative technological success have a strong significant effect on knowledge transfer asymmetry. The inverse Mill's ratio, however, does not become significant in any of the regressions, eliminates our endogeneity concerns.

Models 2 through 7 test each hypothesis individually while model 8 presents the full regression model. Model 2 provides strong evidence for H1b while rejecting H1a: a firm learns relatively more from an R&D alliance when it teams up with a larger organization. While the economic significance of this result is rather small (one standard deviation decrease in relative

size increases net learning by only a tenth of a standard deviation of knowledge transfer

asymmetry), the result is significant at the 1% level. Model 3 shows how relative larger slack

resources increase asymmetric learning, supporting H2. This result loses some significance in the

full regression (model 8), but it remains significant at the 5% level. Surprising, the relative R&D

intensity of alliance partners has no effect on learning asymmetries: model 4 fails to provide

support for H3. As expected, model 5 demonstrates that relative technological diversity (in

support of H4) increases asymmetric knowledge transfer in favor of the more diverse firm.

Models 6 and 7 do not provide support for H5 and H6, respectively. Alliance experience does not

seem to benefit either partner. In addition, the relatedness of the alliance may lead to

inconclusive results because learning opportunity and learning ability trade off equally.

INSERT TABLES 2 AND 3 HERE

Table 3 reports the regression results that test H7 regarding the moderation effect of joint

ventures. Interaction variables are based on mean-centered values of the independent variables to

reduce multicollinearity issues. As Table 3 shows, the results for the direct effects are similar in

terms of significance and coefficient size to Table 2, which means our results are quite stable.

We find only one interesting interaction effect, namely the interaction between relative

firm size and the structural arrangement of an alliance (model 9 in Table 3). While alliances are

generally more favorable for the smaller alliance partner (see H1 above), the formation of a joint

venture reverses this relationship. As depicted below in Figure 1, the smaller partner benefits

from contractual arrangements while the larger partner gains from joint venture agreements.

Significant interaction effects for R&D intensity (model 11) and knowledge diversity (model 12)

lose significance in the full regression (model 15) and are therefore disregarded.

INSERT FIGURE 1 HERE

Robustness checks

We perform two sets of robustness checks. First, though the usual checks did not report any issues, the regressions are repeated using more robust methods. We are well aware of the strict assumptions underlying OLS and wish to make a convincing argument for our findings. For that reason, the regressions are repeated with robust GLM and FGLS models. GLM maximum likelihood technique with robust standard errors is used to correct for potential multicollinearity since VIF statistics for the inverse Mill's ratio and year dummies are above 10. FGLS is used to correct for potential heteroskedasticity. The results, which are excluded here for space reasons, are not different from earlier OLS findings.

Second, we try to dissect the elements of value creation and value capturing in interorganizational collaboration by using three different dependent variables: total knowledge transfer, knowledge inflows, and knowledge outflows. For total knowledge flows, the dependent variable is the combined fraction of citations of both firms after alliance formation, which theoretically ranges from 0 to 2. We also add extra control variables, namely the combined independent variables (the sum of firms' assets, slack resources, etc.). For knowledge inflow and outflow, we move the level of analysis to the firm-alliance and measure the fraction of citations of the focal firm or partner firm after alliance formation, which theoretically range between -1 and 1. Here we also add extra control variables, namely the absolute value of independent variables (focal firm assets, slack resources, etc.). Since the dependent variables are all bounded and there are a substantial number of zeros, a tobit regression is used.

INSERT TABLE 4 AROUND HERE

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The results are included in Table 4. Firm size has a positive effect on total knowledge transfer by significantly increasing knowledge outflows, but it does not change knowledge inflows. This supports the earlier finding that size differences are beneficial, but only to the smaller alliance partner. Slack resources have an opposite effect: they significantly increase total knowledge transfer by increasing knowledge inflows for firms with more slack. The earlier analysis found no significant effect of relative R&D intensity on asymmetric learning. Here it shows that R&D intensity has no effect on overall interfirm learning or outflows, but slightly reduces inflows. Knowledge diversity of a firm increases both elements of knowledge transfer, inflows and outflows. So while earlier results revealed that diverse firms learn more, less diverse firms still benefit from collaborating. Earlier we found no significant effect for alliance experience because it equally increases inflows and outflows of partners. Alliance industry proximity has no effect on either inflows or outflows. The inverse Mill's ratio is significant in all regressions, meaning that self-selection into certain alliances could have biased the results here.

DISCUSSION

This study was motivated by a lack of empirical research on learning competition within R&D alliances. Past literature has extensively examined factors that accelerate or inhibit interfirm learning and knowledge transfer in R&D alliances as well as factors that increase or reduce knowledge inflows (Easterby-Smith et al., 2008; Van Wijk et al., 2008). However, alliance managers are far more concerned about the threat R&D alliances can create for an organization caused by intended and unintended knowledge outflows (Hamel, 1991). First, partner firms may be able to full capture the value jointly created as a result of faster learning mechanisms or complementary resources (Lavie, 2006). Secondly, a partner may, unintendedly,

obtain access to proprietary knowledge and valuable IPR (Kale et al., 2000). These resources are of strategic importance for a firm and sharing these with other organizations form a direct competitive threat.

Therefore, we ask what characteristics of firms and alliances lead to asymmetric, i.e. imbalanced knowledge transfer in R&D alliances. We identify three firm-specific factors that are commonly related to firm innovation or interorganizational learning, but for which the direction of knowledge flows is unknown. Firstly, firm size ordinarily increases knowledge transfer in R&D alliances because firms have more resources available for joint R&D (Van Wijk et al., 2008). Larger firms also possess more knowhow and expertise which alliance partners may acquire. Our analysis, however, has shown that difference in firm size among alliance partners has an unanticipated effect on knowledge transfer: smaller firms learn significantly more from R&D alliances than their partners. Whereas firm size increases alliance value creation, it reduces a firm's ability to appropriate these benefits.

Furthermore, slack resources are commonly associated with firm innovation as well as interfirm learning (Nohria & Gulati, 1996; Patzelt et al., 2008). Non-necessary financial and human capital allows firms to experiment with new techniques and technologies. This serendipitous process eventually increases firm innovation. Such firms can also spend more time and resources on alliances which increases interorganizational learning. This study reveals that interfirm learning facilitated by slack resources mainly benefits the partner owning them: slack resources increase knowledge inflows, but do not effect knowledge outflows. Differences in slack resources among R&D alliance partners therefore lead to asymmetric knowledge transfer in such a way that the partner increasing value creation also increases value appropriation.

Lastly, technological diversity and absorptive capacity lead to imbalanced learning. Diversity in knowledge and knowhow accelerate the assimilation of related knowledge residing outside the organization (Cohen & Levinthal, 1990). It has shown that absorptive capacity and knowledge diversity increase learning in interorganizational alliances (Chen, 2004). As we expected, this advantage is lopsided and favors alliance partners with higher technological diversity. This means that a firm does gain less (potentially even nothing) from collaborating with diverse partners.

The structural arrangement of an alliance moderates these effects. Generally equity-based partnerships involve closer collaboration among partner firms and increase knowledge and information sharing (Mowery et al., 1996). Whereas we therefore expected a positive moderation effects, surprisingly we found the opposite: the negative effect of firm size reverses when alliances are structured as joint ventures. Normally, firms learn more when their alliance partners are larger firms, but in the case of joint ventures the larger alliance partner appropriates a larger fraction of the knowledge flows. The result, graphically depicted in Figure 1, shows that this effect increases with relative firm size but is equal when firms are of comparable size.

Theoretical and Managerial Implications

These results have direct theoretical and empirical implications. A vast amount of academic literature has described the factors that facilitate learning and knowledge transfer in alliances (Easterby-Smith et al., 2008). However, this study has shown that factors increasing knowledge inflows may equally increase knowledge outflows, thereby potentially harming the competitive position of a firm. Instead, we argue that research should strongly differentiate between value creation, i.e. the cumulative amount of learning and knowledge transfer, and value

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appropriation, i.e. the fraction of this amount going to each alliance partners while accounting for the costs of unintended knowledge outflows (Inkpen, 2000; Lavie, 2006). Secondly, our findings talk to recent research on assortative matching in alliance formation. This research has argued that firms ally with partners of similar stature so that each party benefits equally (Ahuja, 2000b). While we control for matching, we still observe large differences among alliance partners which then lead to asymmetric outcomes. Finally, this study provides an empirical examination of learning races in alliances. Qualitative studies and conceptual work had already emphasized the competitive elements present in collaborative relationships (Hamel, 1991; Khanna et al., 1998). Here we find that structural differences among alliance partners change their motivation, opportunity and ability to learn which gives rise to asymmetric outcomes.

For practitioners, the findings of this paper provide some insights in antecedents of asymmetric learning. First, partner selection is an important step in preventing imbalanced value appropriation. While partners are normally selected on their ability to increase value creation, managers should also evaluate characteristics that indicate unreasonable value appropriation, like partner's absorptive capacity and slack resources. Second, the negotiation of an alliance agreement and the structural arrangement in particular are important factors. While joint ventures are normally a tool for learning and knowledge absorption, managers should take into account how it also leads to knowledge outflows. We do not want to ignore the relevance of management of on-going collaborations, but the origins of imbalanced learning that are identified in this study are already fixed before this stage, namely during partner selection and contractual agreements.

CONCLUSION AND LIMITATIONS

Firms have strong incentives to use R&D alliances as tools for learning and obtaining new knowledge. While complementary resources and technologies combined with intended knowledge spillovers foster collaboration among alliance partners, unintended knowledge spillovers and learning races introduce a competitive element in interfirm collaboration. As Hamel (1991) observed in interviews with R&D managers: "[alliance] partners clearly regarded their alliances as transitional devices where the primary objective was the internalization of partner skills". The results of this study indicate that imbalanced learning in R&D alliances is in fact common and systematic. This study analyzed how differences in partner size, structure and strategy provide them with capabilities that increase their knowledge inflows while minimizing their knowledge outflows.

The findings of this study should be interpreted while observing its limitations. First, we use alliance data from SDC Platinum which is known to be incomplete (Lavie, 2007). However, as Schilling (2009) argues, the missing data is largely random and only introduces noise in the analysis. Random incomplete data means we under-estimate certain alliance variables and over-estimate their impact, but results will remain significant. Second, we rely heavily on patent data to measure knowledge flows. We selected the sample of R&D alliances and partners such that patents could serve as proxies for learning and knowledge transfer, but agree that this method is not perfect. Third, while we control for the selection bias in alliance formation, we do not control for managerial choice in alliance structure. This puts the interaction effect of partners' size and alliance structure in question. However, when we checked the two subsamples (i larger than j; j larger than i) individually, we found the correlation between relative size and joint venture

agreements to be close to zero. This means that structure is seemingly unrelated to size

differences between alliance partners.

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Word count: 10,536 words

TABLE 1 – DESCRIPTIVE STATISTICS

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Asymmetry	1.000																		
2. Relative size (assets)	-0.361	1.000																	
3. Relative slack resources	0.213	-0.436	1.000																
4. Relative R&D intensity	0.100	-0.578	0.222	1.000															
5. Relative tech. diversity	-0.218	0.618	-0.205	-0.282	1.000														
6. Relative all. experience	-0.329	0.723	-0.299	-0.322	0.593	1.000													
7. Relative industry proximity	-0.043	-0.042	0.033	-0.033	0.008	-0.039	1.000												
8. Joint venture	-0.033	0.036	-0.033	-0.038	0.023	0.018	-0.048	1.000											
9. Buyer-supplier relationship	-0.042	0.052	-0.040	-0.077	0.034	0.012	0.052	-0.043	1.000										
10. Spatial distance (ln)	0.061	-0.064	-0.023	0.021	-0.030	-0.063	-0.004	0.012	0.022	1.000									
11. Alliance inv. licensing	0.002	-0.016	-0.025	-0.010	0.008	-0.044	0.005	-0.112	-0.022	-0.034	1.000								
12. Alliance inv. downstream	0.005	0.076	-0.031	-0.052	0.110	0.050	0.049	0.037	0.114	0.092	0.018	1.000							
13. Alliance based in Canada	-0.005	0.007	0.004	-0.048	0.009	0.017	0.012	0.043	-0.027	-0.076	-0.035	0.007	1.000						
14. Number of partners in all.	-0.032	0.065	-0.005	-0.041	0.033	0.045	-0.025	0.111	-0.013	-0.017	-0.215	-0.185	-0.021	1.000					
15. Partner had prev. alliance	0.010	0.020	0.011	0.015	0.017	0.035	-0.032	0.009	-0.050	-0.073	-0.096	-0.159	-0.007	0.216	1.000				
16. Pre-alliance asymmetry	0.567	-0.297	0.132	0.103	-0.172	-0.269	-0.059	-0.089	0.000	0.015	-0.001	0.012	-0.076	-0.019	0.038	1.000			
17. Relative tech. success	-0.385	0.674	-0.240	-0.273	0.769	0.693	0.021	0.035	0.012	-0.062	0.003	0.048	0.016	0.078	0.024	-0.309	1.000		
18. Total knowledge transfer	-0.007	0.062	-0.060	-0.015	0.016	0.031	-0.026	-0.081	-0.039	0.011	0.070	-0.044	-0.072	0.081	0.281	0.071	0.040	1.000	
19. Inverse Mill's ratio	0.012	-0.069	0.026	0.053	-0.011	-0.049	0.010	-0.089	-0.003	0.283	-0.050	0.075	0.043	-0.118	-0.336	0.026	-0.062	-0.204	1.000
Mean	0.067	-0.428	0.131	0.011	-0.021	-0.065	-0.053	0.161	0.037	6.558	0.148	0.418	0.018	2.458	0.243	0.002	-0.037	0.670	2.323
Std. dev.	3.700	3.888	1.753	0.290	0.511	0.727	1.943	0.368	0.190	1.932	0.355	0.493	0.134	0.822	0.429	4.589	0.814	1.113	0.533
Min.	-26.963	-11.597	-5	-1.000	-0.987	-1	-4	0	0	0	0	0	0	2	0	-66.655	-1	-3.135	0.447
Max.	27.763	12.028	5	1.000	0.987	1	4	1	1	8.370	1	1	1	5	1	59.087	1	5.398	2.980

N = 989

All correlations larger than |0.0625| are significant at the 5% level.

All correlations larger than |0.080| are significant at the 1% level.

TABLE 2 – OLS REGRESSION FOR DIRECT EFFECTS

Dep. variable: Asymmetry	(model 1)	(model 2)	(model 3)	(model 4)	(model 5)	(model 6)	(model 7)	(model 8)
Relative size (assets)		-0.094**						-0.138**
		(0.033)						(0.047)
Relative slack resources			0.197***					0.143*
			(0.056)					(0.060)
Relative R&D intensity				-0.188				-1.015*
				(0.341)				(0.408)
Relative technological diversity					0.822**			1.046***
					(0.292)			(0.297)
Relative alliance experience						-0.328+		-0.093
						(0.182)		(0.205)
Relative alliance industry proximity							-0.015	-0.041
							(0.049)	(0.049)
Joint venture	0.083	0.091	0.110	0.079	0.076	0.072	0.079	0.064
	(0.269)	(0.268)	(0.267)	(0.269)	(0.268)	(0.269)	(0.269)	(0.266)
Buyer-supplier relationship	-0.756	-0.680	-0.683	-0.778	-0.790	-0.753	-0.752	-0.734
	(0.507)	(0.506)	(0.504)	(0.508)	(0.505)	(0.506)	(0.507)	(0.501)
Spatial distance (ln)	0.105*	0.101+	0.111*	0.104*	0.104*	0.102*	0.104*	0.099+
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.051)
Alliance involves licensing	0.127	0.106	0.139	0.123	0.118	0.092	0.127	0.065
	(0.281)	(0.280)	(0.279)	(0.281)	(0.280)	(0.281)	(0.281)	(0.278)
Alliance involves downstream	0.049	0.083	0.051	0.046	-0.007	0.059	0.050	0.027
	(0.203)	(0.202)	(0.201)	(0.203)	(0.203)	(0.202)	(0.203)	(0.201)
Alliance based in Canada	1.109	1.085	1.103	1.089	1.110	1.106	1.111	0.970
	(0.718)	(0.715)	(0.714)	(0.719)	(0.715)	(0.717)	(0.718)	(0.709)
Number of partners in alliance	-0.018	-0.012	-0.022	-0.021	-0.011	-0.024	-0.018	-0.016
	(0.125)	(0.124)	(0.124)	(0.125)	(0.124)	(0.125)	(0.125)	(0.123)
Partners had previous alliance	-0.040	-0.046	-0.052	-0.035	-0.061	-0.026	-0.041	-0.054
	(0.251)	(0.250)	(0.250)	(0.252)	(0.251)	(0.251)	(0.251)	(0.248)
Pre-alliance asymmetry	0.410***	0.402***	0.405***	0.410***	0.404***	0.407***	0.410***	0.385***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Relative technological success	-1.028***	-0.746***	-0.933***	-1.045***	-1.434***	-0.832***	-1.028***	-1.098***
	(0.123)	(0.158)	(0.125)	(0.127)	(0.189)	(0.164)	(0.123)	(0.211)
Total knowledge transferred	-0.147	-0.130	-0.121	-0.148	-0.141	-0.144	-0.147	-0.099
	(0.092)	(0.092)	(0.091)	(0.092)	(0.091)	(0.092)	(0.092)	(0.091)
Inverse Mill's ratio	-0.299	-0.309	-0.287	-0.295	-0.320	-0.295	-0.298	-0.301
	(0.226)	(0.225)	(0.225)	(0.226)	(0.225)	(0.226)	(0.226)	(0.223)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-0.697	-0.589	-0.518	-0.695	-0.421	-0.454	-0.716	-0.029
	(1.559)	(1.554)	(1.551)	(1.560)	(1.557)	(1.563)	(1.561)	(1.548)
Observations	989	989	989	989	989	989	989	989
R-squared	0.381	0.386	0.388	0.381	0.386	0.383	0.381	0.402

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

TABLE 3 – OLS REGRESSION FOR MODERATED EFFECTS

Dep. variable: Asymmetry	(model 9)	(model 10)	(model 11)	(model 12)	(model 13)	(model 14)	(model 15)
Relative size (assets)	-0.084*						-0.129**
	(0.034)						(0.047)
Relative slack resources		0.202***					0.162**
		(0.056)					(0.061)
Relative R&D intensity			-0.374				-1.277**
			(0.351)				(0.416)
Relative technological diversity				0.865**			1.062***
				(0.291)			(0.297)
Relative alliance experience					-0.332+		-0.046
					(0.182)		(0.206)
Relative alliance industry proximity						-0.011	-0.034
						(0.049)	(0.049)
Joint venture x Relative size	0.162*						0.279*
	(0.079)						(0.121)
Joint venture x Relative slack		0.112					0.347+
		(0.171)					(0.193)
Joint venture x Relative R&D intensity			-2.570*				-1.902
			(1.185)				(1.323)
Joint venture x Relative knowledge diversity				1.375*			0.693
				(0.568)			(0.665)
Joint venture x Relative alliance experience					0.190		-0.649
					(0.360)		(0.487)
Joint venture x Relative industry proximity						0.080	0.079
						(0.149)	(0.147)
Joint venture	0.064	0.119	0.032	0.047	0.071	0.094	0.011
	(0.268)	(0.268)	(0.270)	(0.268)	(0.269)	(0.271)	(0.267)
Buyer-supplier relationship	-0.651	-0.690	-0.742	-0.740	-0.744	-0.742	-0.685
	(0.505)	(0.504)	(0.508)	(0.504)	(0.507)	(0.508)	(0.500)
Spatial distance (ln)	0.099+	0.111*	0.103*	0.098+	0.102*	0.104*	0.094+
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.051)
Alliance involves licensing	0.111	0.141	0.146	0.143	0.091	0.126	0.113
	(0.279)	(0.279)	(0.281)	(0.279)	(0.281)	(0.281)	(0.277)
Alliance involves downstream	0.095	0.058	0.035	0.015	0.060	0.048	0.068
	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)	(0.203)	(0.201)
Alliance based in Canada	1.015	1.141	1.006	0.923	1.093	1.114	0.845
	(0.715)	(0.716)	(0.718)	(0.718)	(0.718)	(0.718)	(0.713)
Number of partners in alliance	-0.028	-0.022	-0.016	-0.014	-0.026	-0.021	-0.034
	(0.124)	(0.124)	(0.125)	(0.124)	(0.125)	(0.125)	(0.123)
Partners had previous alliance	-0.044	-0.050	-0.023	-0.058	-0.033	-0.036	-0.002
	(0.250)	(0.250)	(0.251)	(0.250)	(0.252)	(0.252)	(0.248)
Pre-alliance asymmetry	0.408***	0.405***	0.415***	0.405***	0.408***	0.410***	0.396***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Relative technological success	-0.742***	-0.935***	-1.022***	-1.427***	-0.824***	-1.025***	-1.103***
	(0.158)	(0.125)	(0.127)	(0.189)	(0.165)	(0.123)	(0.211)
Total knowledge transferred	-0.125	-0.122	-0.149	-0.142	-0.141	-0.147	-0.101
	(0.091)	(0.091)	(0.092)	(0.091)	(0.092)	(0.092)	(0.091)
Inverse Mill's ratio	-0.299	-0.288	-0.283	-0.307	-0.292	-0.294	-0.276
	(0.225)	(0.225)	(0.226)	(0.225)	(0.226)	(0.226)	(0.222)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-0.645	-0.407	-0.708	0.143	-0.536	-0.625	0.854
	(1.552)	(1.560)	(1.557)	(1.570)	(1.571)	(1.571)	(1.593)
Observations	989	989	989	989	989	989	989
R-squared	0.388	0.389	0.384	0.389	0.383	0.381	0.412

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

TABLE 4 – KNOWLEDGE INFLOWS AND OUTFLOWS

Dependent variable:	(model 16) Knowledge transfer	(model 17) Knowledge transfer	(model 18) Knowledge inflow	(model 19) Knowledge inflow	(model 20) Knowledge outflow	(model 21) Knowledge outflow
Size (assets)[1]		0.161*		-0.064		0.198***
		(0.072)		(0.062)		(0.060)
Slack resources[1]		0.394***		0.316***		0.099
		(0.106)		(0.090)		(0.091)
R&D intensity[1]		0.225		-1.265*		0.716
		(0.704)		(0.640)		(0.606)
Technological diversity[1]		2.334***		2.217***		2.442***
		(0.422)		(0.365)		(0.359)
Alliance experience[1]		0.007***		0.001		0.007***
		(0.001)		(0.001)		(0.001)
Alliance industry proximity[1]		-0.049		-0.057		-0.029
		(0.071)		(0.063)		(0.060)
Alliance strength	-0.525	-0.388	-0.063	0.008	-0.185	-0.234
	(0.433)	(0.445)	(0.252)	(0.262)	(0.253)	(0.245)
Buyer-supplier relationship	-0.274	-0.153	-0.226	-0.174	-0.248	-0.176
	(0.824)	(0.816)	(0.486)	(0.497)	(0.488)	(0.467)
Spatial distance (ln)	0.269**	0.159+	0.214***	0.185***	0.206***	0.151***
	(0.083)	(0.081)	(0.048)	(0.049)	(0.049)	(0.046)
Alliance involves licensing	1.065*	1.344**	0.534*	0.523*	0.588*	0.831***
	(0.436)	(0.442)	(0.256)	(0.263)	(0.257)	(0.248)
Alliance involves downstream	0.147	0.065	0.055	-0.033	0.055	0.011
	(0.326)	(0.326)	(0.191)	(0.196)	(0.191)	(0.183)
Alliance based in Canada	-4.991**	-4.132*	-3.839***	-3.592**	-4.017***	-3.162**
	(1.675)	(1.766)	(1.114)	(1.158)	(1.114)	(1.056)
Number of partners in alliance	-0.042	-0.179	0.014	0.050	0.011	-0.125
	(0.196)	(0.199)	(0.113)	(0.117)	(0.113)	(0.109)
Partners had previous alliance	2.327***	0.691+	1.620***	1.423***	1.600***	0.645**
	(0.368)	(0.388)	(0.212)	(0.223)	(0.212)	(0.206)
Pre-alliance knowledge transfer[1]	0.426***	0.360***	0.478***	0.493***	0.478***	0.346***
	(0.033)	(0.033)	(0.024)	(0.025)	(0.025)	(0.024)
Technological success[2]	-0.201	0.178	0.362***	0.329***	0.071	0.258**
	(0.145)	(0.168)	(0.072)	(0.077)	(0.073)	(0.081)
Inverse Mill's ratio	-3.782***	-2.949***	-2.630***	-2.367***	-2.664***	-2.247***
	(0.360)	(0.390)	(0.205)	(0.219)	(0.206)	(0.202)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)
Sigma	4.105***	3.924***	3.247***	3.259***	3.262***	3.007***
	(0.131)	(0.125)	(0.079)	(0.080)	(0.079)	(0.072)
Constant	0.070	-6.261*	-3.041	-4.188*	-2.015	-5.039**
	(2.830)	(3.125)	(1.916)	(2.009)	(1.878)	(1.896)
Observations	989	989	1,978	1,978	1,978	1,978

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

[1] For model 22 and 23, these variables are the combined measures of both firms, whereas for model 24 to 27 these variables take the value of the focal firm

[2] For model 22 and 23, these variables are the combined measures of both firms, whereas for model 24 to 27 these variables take the value of the partner firm

FIGURE 1 – MODERATION EFFECT OF JOINT VENTURE AGREEMENTS
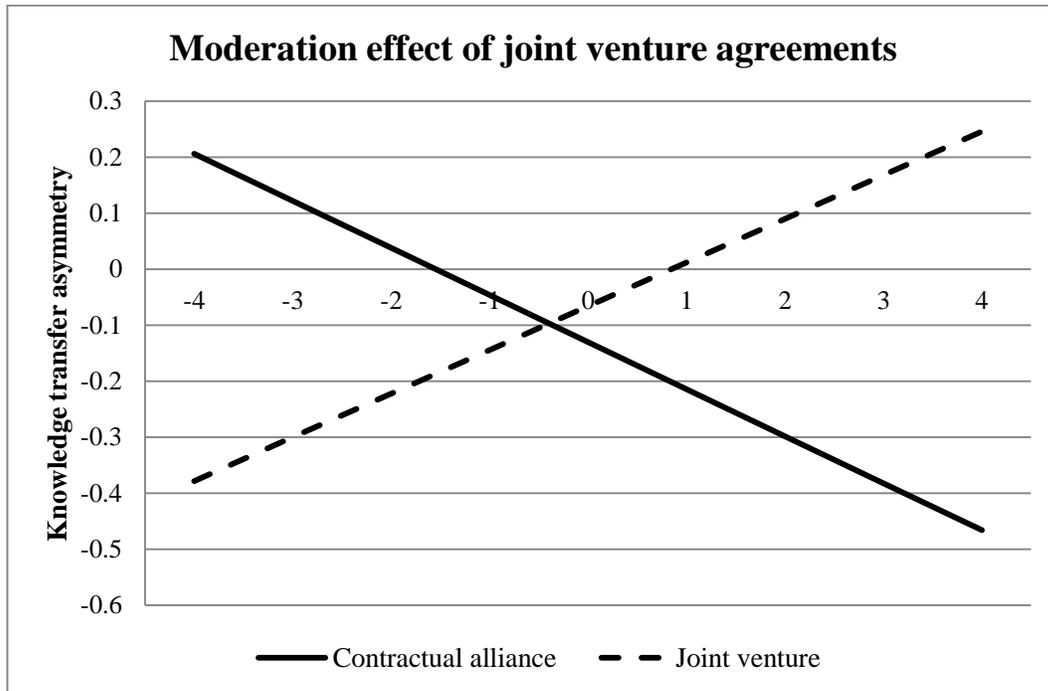
Figure 1 – moderation effect of joint venture agreements (horizontal axis represents relative firm size with an interval one standard deviation from its mean)