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Do the friends of my sister Matter? A study of indirect R&D alliances and scientific performance of MNC subsidiaries

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Abstract
Whereas alliance portfolio literature has focused on the firm-level implications of alliance portfolios, we shift the level of analysis to the subsidiary-level. Relying on insights from social network theory, we make a distinction between direct R&D alliances – i.e. R&D alliances that are formed by the focal R&D subsidiary – and indirect R&D alliances – i.e. R&D alliances that are formed by sister R&D subsidiaries of the same multinational firm. In addition, we hypothesize that the effect of indirect alliances is contingent on overlap in knowledge bases between subsidiaries and their involvement in joint R&D projects. To test our hypotheses, we have created a subsidiary-level panel dataset of 1961 R&D subsidiaries belonging to 117 pharmaceutical and biotechnology firms. Jointly, our findings show that indirect alliances can be an important source of additional knowledge

recombination opportunities for R&D subsidiaries. At the same time, our findings also suggest that, for isolated R&D subsidiaries, indirect alliances might function as a distracting attention structure, negatively influencing scientific performance of such subsidiaries.

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A STUDY OF INDIRECT R&D ALLIANCES AND SCIENTIFIC PERFORMANCE OF MNC SUBSIDIARIES

ABSTRACT

Whereas alliance portfolio literature has focused on the firm-level implications of alliance portfolios, we shift the level of analysis to the subsidiary-level. Relying on insights from social network theory, we make a distinction between direct R&D alliances – i.e. R&D alliances that are formed by the focal R&D subsidiary – and indirect R&D alliances – i.e. R&D alliances that are formed by sister R&D subsidiaries of the same multinational firm. In addition, we hypothesize that the effect of indirect alliances is contingent on overlap in knowledge bases between subsidiaries and their involvement in joint R&D projects. To test our hypotheses, we have created a subsidiary-level panel dataset of 1961 R&D subsidiaries belonging to 117 pharmaceutical and biotechnology firms. Jointly, our findings show that indirect alliances can be an important source of additional knowledge recombination opportunities for R&D subsidiaries. At the same time, our findings also suggest that, for isolated R&D subsidiaries, indirect alliances might function as a distracting attention structure, negatively influencing scientific performance of such subsidiaries.

Keywords: R&D alliances, MNCs, intra-firm network, knowledge recombination, scientific performance.

INTRODUCTION

Firms heavily engage in R&D alliances as they can provide access to external knowledge that is complementary to their internal knowledge base (Deeds & Hill, 1996; Rothaermel & Hess, 2007). In order to benefit from R&D alliances, external knowledge needs to be recombined *within* individual alliances and *across* different alliances in the alliance portfolio (Parise & Casher, 2003; Wassmer & Dussauge, 2011a). However, in their theorizing and testing on how knowledge from R&D partners is recombined, scholars tend to frame the focal firm as a monolithic entity, focusing on the *firm-level* implications of alliance portfolios and largely ignoring that organizations often consist of multiple entities that each can engage in alliance activities. In the particular context of multinational companies (MNCs), several studies (e.g. Alnuaimi, Singh, & George, 2012; Bos, Faems, & Noseleit, 2014; Zaheer & Hernandez, 2011) have observed that not only the headquarters but also its geographically dispersed subsidiaries engage in alliances. In this study, we therefore shift attention from the firm-level to the subsidiary-level, examining the subsidiary performance implications of alliances portfolios.

This shift is important as it allows us to study the interaction between the external network (i.e. portfolio of alliances) and the intra-firm network (i.e. collection of subsidiaries). Existing MNC literature consistently shows that subsidiaries are affected by the behavior of sister subsidiaries belonging to the same MNC network (Gupta & Govindarajan, 1994). We therefore expect that R&D alliances not only provide direct alliance knowledge recombination possibilities to the subsidiary that engages in the R&D alliance, but may also provide indirect benefits to other subsidiaries. Relying on insights from social network theory (e.g. Ahuja, 2000; Hansen, 2002), we make a conceptual distinction between direct alliances (e.g. formed by the focal subsidiary itself) and indirect alliances (e.g. formed by sister subsidiaries that belong to the same MNC) and theorize on their performance implications for subsidiaries. In addition, we expect that not all subsidiaries benefit to the same extent from indirect alliances as, even within firms, knowledge transfer is a complex process (Teece, 1977, Monteiro, Arvidsson, & Birkinshaw, 2008; Van Wijk, Jansen, Van den Bosch, & Volberda, 2012). Relying on insights from the knowledge-based view (KBV), we identify potential contingency effects. In particular, we investigate how the overlap in the scientific knowledge base between R&D subsidiaries and the joint involvement of the focal subsidiary and sister subsidiaries in R&D projects moderate the relationship between indirect alliances and subsidiary scientific performance.

In sum, the purpose of this paper is to test (i) the impact of direct and indirect alliances on the scientific performance of subsidiaries and (ii) the moderating impact of the internal subsidiary network structure. In order to do so, we have developed a novel panel data set on 1961 R&D subsidiaries belonging to 117 pharmaceutical and biotechnology firms covering nine years (1995-2003). We rely on scientific publications to construct indicators of firms' internal research network and the scientific performance of subsidiaries. Data on R&D alliance announcements are used to measure the direct and indirect alliances of firms' subsidiaries.

The results of our study provide evidence that indirect alliances can positively influence the scientific performance of focal subsidiaries, suggesting that indirect alliances are important sources for additional knowledge recombination opportunities. At the same time, we show that such indirect knowledge recombination opportunities can only be realized when focal and sister subsidiaries share sufficient overlap in their knowledge base or engage in joint R&D projects. Our findings also point to an unexpected dark side of indirect R&D alliances. In particular, we observe that, for isolated R&D subsidiaries – i.e. subsidiaries with limited knowledge overlap and connections with other subsidiaries in the MNC network –, the number of indirect alliances negatively influences their scientific performance. These latter findings suggest that, for these particular subsidiaries, indirect alliances actually function as distracting attention structures.

We contribute to the alliance literature by increasing our understanding of how firms benefit from R&D alliances. While Wassmer and Dussauge (2011a) make an important distinction between value creation at the single alliance-level and at the alliance-portfolio-level, we make an additional and complementary distinction between direct and indirect alliance knowledge recombination. Second, through explicitly acknowledging the dispersion of alliances among different organizational entities, our study contributes to emerging insights on the interaction between intra-firm and inter-firm knowledge networks. Third, by shifting our attention to a different level of analysis (i.e. from firm-level to subsidiary-level), we are able to reveal patterns of value creation and destruction from alliances that are not visible at the firm-level.

The remainder of this paper is structured as follows. First, we discuss knowledge recombination from alliance portfolios and introduce the distinction between direct and indirect alliances. Next, we develop hypotheses on the effect of indirect alliances on the scientific performance of subsidiaries. Subsequently, we explain our methodological approach and present the findings of our empirical analyses. Finally, we discuss the main implications of our findings, point to the main limitations of our research and offer suggestions for future studies.

ALLIANCE PORTFOLIOS: STATE OF THE ART

In this section, we first discuss existing firm-level insights on the knowledge recombination implications of alliance portfolios. Subsequently, we shift to the subsidiary-level and make an additional distinction between direct and indirect alliance knowledge recombination.

Firm-Level Perspective: Single versus Portfolio Alliance Knowledge Recombination

To explain the performance implications of alliance portfolios, scholars (Vasudeva & Anand, 2011; Zheng & Yang, 2015) consistently point to the mechanism of knowledge recombination. New knowledge can either be created by novel recombinations of existing knowledge elements or novel configurations to link elements with each other (Galunic & Rodan, 1998; Yang, Phelps, & Steensma, 2010). However, over time, the firm's knowledge base might get depleted or the necessary knowledge for certain combinations is not available in-house and too costly to develop or acquire (Rothaermel & Hess, 2007; Vasudeva & Anand, 2011). R&D alliances can provide firms with access to new knowledge elements and thereby create new knowledge recombination possibilities (Deeds & Hill, 1996; Hess & Rothaermel, 2011), which increases the likelihood of new discoveries (Quintana-García & Benavides-Velasco, 2011).

Insert Figure 1 about here

According to Wassmer and Dussauge (2011a), firms can create value from R&D alliances on two different levels, as illustrated in Figure 1. First, value can be created *within* a single alliance by recombining the knowledge of the external partner with the firm's own knowledge (Cohen & Levinthal, 1990; Hagedoorn & Wang, 2012). For instance, within alliance *ij*, resource R_{i1} of focal firm *i* can be recombined with resource R_{j1} of firm *j*. Second, value can be created *across* alliances, meaning that firms can recombine resources and knowledge across different alliances in their alliance portfolio (Parise & Casher, 2003; Wassmer & Dussauge, 2011a, 2011b). The potential combination of R_{j1} of firm *j* and R_{h1} of firm *h* with R_{i1} of firm *i* provides additional benefits for the alliance portfolio of focal firm *i*.

Subsidiary-Level Perspective: Direct versus Indirect Alliance Knowledge Recombination

While extant alliance portfolio research has provided important insights into how focal firms can create value within and across R&D alliances, it tends to focus on the firm-level implications of alliance portfolios, ignoring the internal structure of focal firms. Recently, some studies (Grigorio & Rothaermel, in press; Laursen, Moreira, & Markus, 2015) started addressing this issue, demonstrating that the structure of the internal co-inventor network influences focal firms' ability and speed to recombine knowledge from external knowledge sourcing strategies such as alliances, acquisitions, and licensing. Whereas these latter studies still focus on the firm-level implications, we shift attention to the subsidiary-level of analysis, allowing us to enrich our understanding of alliance knowledge recombination processes by making a conceptual distinction between direct and indirect alliance knowledge recombination.

Subsidiaries within MNCs operate as semi-independent entities, have different missions and heterogeneous stocks of knowledge. However, they are connected with each other through an intra-firm network of ties, which implies that the behavior and actions of a particular subsidiary can impact their sister subsidiaries (Ambos & Ambos, 2009; Gupta & Govindarajan, 1994). We therefore expect that a R&D alliance, next to providing direct knowledge recombination possibilities to the subsidiary that initially formed the alliance, may provide indirect benefits to sister subsidiaries. As illustrated in Figure 2, subsidiary 3 of firm *i* can directly recombine alliance knowledge on the single alliance-level and on the alliance portfolio-level. In addition, as illustrated by the dotted arrows, subsidiary 1 of firm *i* may indirectly benefit from the alliances of subsidiary 3 of firm i, because both subsidiaries are part of same intra-firm network.

Insert Figure 2 about here

In the next section, we rely on insights from social network theory to hypothesize on the effect of indirect alliances on the scientific performance of subsidiaries. In addition, applying insights from the knowledge based view, we propose two variables (i.e. knowledge overlap and joint R&D projects) that are likely to moderate this effect.

HYPOTHESES

Indirect Alliances and the Scientific Performance of Subsidiaries

Social network scholars have studied the implications of indirect ties at different levels of analysis, such as the individual- (Singh, 2005), the business unit- (Hansen, 2002), and the firm-level (Ahuja, 2000; Salman & Saives, 2005). In general, this literature emphasizes that focal actors can benefit from their indirect network as indirect ties entail important knowledge gathering and processing benefits.

Generating novel scientific output requires access to a broad pool of knowledge. Social network scholars point to the indirect network as an important knowledge gathering instrument. Salman and Saives (2005), for instance, describe the indirect network as “a shadow database of diverse information” (p. 212), which can be an effective source of competitive advantage. Ahuja (2000) argues that firms with many indirect contacts receive information about successes and failures in similar research efforts conducted by other firms (Ahuja, 2000; Burt, 1992).

Accordingly, firms can conduct their research more effectively by avoiding certain paths and by continuing to invest in promising avenues.

Next to facilitating access to knowledge, the indirect network also acts as a knowledge processing device. Each additional node that an actor has access to can serve as an information-processing mechanism by absorbing, sifting and classifying new developments (Ahuja, 2000; Salman & Saives, 2005). In this way, the indirect network serves as a filtering device for relevant knowledge about new opportunities at an early stage (Burt, 1992). Moreover, in indirect networks, one is more likely to find weak ties, which are less likely to provide redundant information (Granovetter, 1973; Hansen, 1999).

Applying these established insights to our particular setting, we argue that subsidiaries not only benefit from their own direct R&D alliances, but may also benefit from indirect R&D alliances that are formed by their sister subsidiaries. In particular, we argue that subsidiaries, which have many indirect alliances, are likely to have higher knowledge gathering and processing capacity than subsidiaries whose indirect alliance network is more restricted. We therefore expect that, as the number of indirect R&D alliances increases, R&D subsidiaries experience more knowledge recombination opportunities, which subsequently improves their scientific performance.

H_1: The number of indirect R&D alliances is positively related to the scientific performance of the focal subsidiary.

At the same time, we expect that indirect alliances have a smaller effect on the scientific performance of subsidiaries than direct alliances. Direct ties are considered to be more efficient in transferring knowledge as they are characterized by more frequent communication and higher levels of trust, which increases the ability and motivation to share knowledge between partners

(Singh, 2005). Transferring knowledge via intermediaries, such as other subsidiaries, can cause incompletion, distortion and delays (Singh, 2005; Zhao & Anand, 2013), reducing the likelihood of subsequent successful knowledge recombination. In comparison to direct ties, indirect ties are therefore considered less efficient conduits for knowledge recombination (Hansen, 2002). Hence, we propose the following hypothesis:

> *H_2: The positive relationship between the number of indirect R&D alliances and the scientific performance of the focal subsidiary is less outspoken than the positive relationship between the number of direct R&D alliances and the scientific performance of the focal subsidiary.*

Extant alliance portfolio literature (e.g. Rothaermel & Deeds, 2006; Deeds & Hill, 1996) has also pointed to potential non-linear effects of the number of alliances on firm performance. These studies have argued that the ability to simultaneously manage different alliances might be restricted because of cognitive constraints and alliance management overload. In their study, Deeds and Hill (1996), for instance, find that beyond a certain threshold of 25 alliances, forming additional alliances hurts firm performance. Whereas they examined the firm-level implications of the number of alliances, we instead focus on the subsidiary-level implications. As alliances are dispersed across different subsidiaries, it is less likely that, for a particular subsidiary, the tipping point is reached where the disadvantages of alliance portfolio size become more outspoken than the advantages. We therefore do not expect a priori non-linear effects of direct and indirect alliances. Nevertheless, we conduct robustness tests to check whether there is evidence for a non-linear relationship in our context.

Moderating Effects

We expect that not all R&D subsidiaries benefit to the same extent from indirect R&D alliances. Relying on insights from the knowledge-based view (KBV), we argue that, in order to realize knowledge recombination benefits from indirect R&D alliances, the knowledge first needs to be transferred from the sister subsidiary that formed the R&D alliance to the focal subsidiary. Even within firms, transferring knowledge has been identified as a complex process (Teece, 1977) as each subsidiary is locally embedded in its specific environment and has a particular history of transferring and recombining knowledge (Monteiro et al., 2008; Van Wijk et al., 2012). We therefore expect heterogeneity in the extent to which indirect alliance knowledge is transferred between subsidiaries. Relying on insights from this KBV literature, we point to two potential moderators of the relationship between indirect alliances and the scientific performance of subsidiaries: knowledge overlap between subsidiaries and their involvement in joint R&D projects.

Knowledge overlap. We expect that overlap in scientific knowledge bases between the sending sister unit and the receiving focal subsidiary unit increases the ability of the focal subsidiary to benefit from the alliances that are formed by the sister subsidiary. Overlap in knowledge implies that two parties possess, to a certain extent, common knowledge, which facilitates the transfer of knowledge between them (Grant, 1996).

Overlap in knowledge bases improves knowledge transfer by facilitating communication and coordination between the sender and receiver (Makri, Hitt, & Lane, 2010). It reduces causal ambiguity, creates a common ground between both parties and facilitates learning (Parmigiani & Holloway, 2010). Moreover, common knowledge implies that the knowledge-processing systems of both parties function in a similar way. Because they have experience with solving similar types of problems, it will be easier to find new knowledge recombination possibilities for the incoming knowledge (Lane & Lubatkin, 1998). Carnabuci and Operti (2013) have shown that, when the knowledge bases of two inventors are too different, cognitive barriers between both parties will arise, making it difficult to understand each other and to successfully transfer knowledge between both parties.

Applying these insights, we expect that overlap in knowledge bases between the sending sister unit and the receiving focal subsidiary unit facilitates the extent to which the focal subsidiary can realize knowledge recombination opportunities originating from indirect alliances. The common knowledge base of the sister and focal subsidiary facilitates the transfer of novel information from the indirect alliance partner. Moreover, as the sister and focal subsidiary have experience with solving similar problems, the likelihood that the focal subsidiary actually recombines the incoming knowledge also increases. Therefore, we state the following hypothesis:

H_3: The level of knowledge overlap between the focal subsidiary and the sister units that form R&D alliances positively moderates the relationship between the number of indirect R&D alliances and the scientific performance of the focal subsidiary unit.

Internal joint R&D projects. Next to knowledge overlap, we also expect that the strength of the ties between subsidiaries will facilitate the transfer of the knowledge from indirect alliances. While all subsidiaries are linked with each other via the intra-MNC network, some subsidiaries are more strongly connected than others (Bouquet & Birkinshaw, 2008; Gupta & Govindarajan, 1994). According to Granovetter (1973: 1361), strong ties reflect a “combination of the amount of time, the emotional intensity, the intimacy and the reciprocal services which characterize the tie”. A number of recent network studies (e.g. Alnuaimi et al., 2012; Carnabuci & Operti, 2013; Funk, 2014; Parachuri & Eisenman, 2012) have measured the characteristics of intra-firm networks via the involvement in joint R&D projects. The involvement in joint R&D projects creates strong ties between the involved parties as it implies extensive interaction between the parties (Parachuri, 2010). Frost and Zhou (2005), for instance, found that subsidiaries of MNCs are more likely to exchange knowledge if they engaged in joint R&D projects in the past. When two parties are strongly connected, the knowledge sender is also more motivated to spend time and effort in ensuring that the knowledge seeker sufficiently understands the transferred knowledge. Strong ties are therefore seen as viable mechanisms to transfer tacit and complex knowledge (Alnuaimi et al., 2012; Hansen, 1999; Tortoriello, Raegans, & McEvily, 2012). Finally, strong ties facilitate the development of trust (Levin & Cross, 2004), which increases the willingness to share knowledge (Sankowska, 2013; Tsai & Ghoshal, 1998).

Applying these insights, we make a conceptual distinction between connected indirect alliances (i.e. indirect alliances formed by sister subsidiaries with which the focal subsidiary is engaged in joint R&D projects) and unconnected indirect alliances (i.e. indirect alliances formed by sister subsidiaries with which the focal subsidiary has no joint R&D project) and we expect that, because of the knowledge transfer advantages that are associated with strong ties, it is easier to realize knowledge recombination benefits from connected indirect alliances than from unconnected indirect alliances. This results in the following hypothesis:

H4: The number of connected indirect R&D alliances has a stronger positive relationship with the scientific performance of a focal subsidiary than the number of unconnected indirect R&D alliances.

Interplay between knowledge overlap and internal joint R&D projects. Combining the effects of knowledge overlap and internal joint R&D projects, we expect that knowledge overlap is especially important in the setting of unconnected indirect alliances. The involvement in joint R&D projects facilitates the creation of joint routines and mutual trust (Kale, Dyer & Singh, 2002; Levin & Cross, 2004; Zollo, Reuer, & Singh, 2002), creating a behavioral and cognitive foundation for the future transfer of knowledge. Even if there is limited overlap in the knowledge bases of sending and receiving subsidiaries, the willingness and motivation of subsidiaries with strong ties to transfer knowledge is likely to overcome learning barriers that are linked to limited overlap in knowledge bases (Sankowska, 2013; Tsai & Ghoshal, 1998). In contrast, when two subsidiaries have not collaborated with each other before, we expect that the overlap in knowledge bases becomes an essential factor to ensure that the receiver understands the knowledge that is being transferred. We therefore expect that the moderating effect of knowledge overlap is more outspoken for the relationship between the number of unconnected indirect alliances and the scientific performance of the focal subsidiary. Hence, we hypothesize:

H5: The moderating effect of knowledge overlap is more outspoken for the relationship between the number of unconnected indirect R&D alliances and the scientific performance of the focal subsidiary than for the relationship between the number of connected indirect R&D alliances and the scientific performance of the focal subsidiary.

METHODOLOGY

To test our hypotheses, we created a novel subsidiary-level panel dataset covering 1961 R&D subsidiaries of 117 firms in the pharmaceutical industry over the period 1995-2003. We rely on this industry because of its pronounced R&D activities and the importance of external collaborations (Hagedoorn & Wang, 2012). The sample firms are selected as the 125 highest R&D spending European, US and Japanese firms in the pharmaceutical industry based on the

‘2004 EU Industrial R&D Investment Scoreboard’. This list is complemented with the 31 largest patentees in biotechnology at the European Patent Office anno 2005. This resulted in an initial sample of 156 pharmaceutical and biotechnology firms. Subsequently, we limited the sample to those 117 firms that had at least one R&D alliance during our sample period.

To create the dataset, we have collected data from different data sources. First, we used information on scientific publications from Thomson Reuters’ Web of Science to identify the R&D units of the sample firms and to operationalize intra-firm collaboration patterns. We used citation-weighted publication counts to measure the scientific performance of R&D subsidiaries. Second, we used the SDC Platinum database to collect information on inter-firm R&D alliances that are formed during the sample period. We assign R&D alliances to subsidiaries to distinguish between direct and indirect R&D alliances.

Identification of R&D Units

Following prior work (Arora, Belenzon, & Rios, 2014; Meyer, 2000), we relied on publication data to measure the internal R&D structures of firms. We started by collecting the full set of publications of the sample firms. Therefore, we search, for each sample firm, for publications under the name of the parent firm as well as all their majority-owned subsidiaries. For this purpose, yearly lists of firms’ subsidiaries reported in corporate annual reports, yearly 10-K filings in the US, and, for Japanese firms, information on foreign subsidiaries published by Toyo Keizai in the yearly ‘Directories of Japanese Overseas Investments’ were used. The consolidation was done on a yearly basis to take into account changes in the group structure of the sample firms due to M&As, green-field investments and spin-offs. Acquired companies, and their stocks of publications, are considered part of a parent firm from the year of acquisition onwards.

We used the author information listed on scientific publications of firms to identify all the subsidiaries that engaged in R&D activities. Using the names and addresses of the firms listed on the scientific publication, we could identify whether they represented the same subsidiary or not (Frenken, Hölzl, & de Vor, 2005; Fabrizio, 2009). Our two main criteria to match publications and R&D subsidiaries were (1) the city location, and (2) the name of the subsidiary. Based on information from annual reports and company websites, we took into account that subsidiary names can change over time. The coding process of the R&D subsidiaries has been conducted twice by the first author, e.g. during February-April 2014 and during September-November 2014. The results of the first and second coding were highly similar (a correlation of 0.96). Subsequently we assigned publications to specific subsidiaries and we calculated the number of publications for each subsidiary in the past five years. If a subsidiary had no publications during this time period, it was labeled as an ‘R&D-inactive’ subsidiary, and was not included in the analysis for this year. This resulted in a final sample of 1961 R&D subsidiaries belonging to 117 firms. In total, our dataset comprises 11794 R&D subsidiary-year observations.

Dependent Variable: Subsidiary Scientific Performance

To measure the performance of R&D subsidiaries, we use a citation-weighted publication count.. The variable *Subsidiary scientific performance* is calculated as the sum of the number of publications and the number of forward citations to the publications of a focal R&D subsidiary. We used a fixed four-year window to calculate the forward citations. It is important to note that we depart from the existing literature[1], which frequently used patents to measure the performance of R&D activities (e.g. Almeida & Phene, 2004; Lahiri & Narayanan, 2013; Della Malva, Kelchtermans, Leten, & Veugelers, 2015). The main reason for this is that it is difficult to identify the origin of patents in a MNC. The patent applicant can be the subsidiary that developed the invention, but it can also be another subsidiary of the firm that is responsible for patent filings or which owns the patent for fiscal or other considerations (OECD, 2009; Griffith, Miller, & Connell, 2014; Bergek & Bruzelius, 2010). In case of publications, the authors typically mention the name of the institution where the knowledge was generated rather than the firm's IP department or another subsidiary (Jaffe, 1986; Rothaermel & Hess, 2007). Scientific publications are therefore more reliable to link to specific R&D subsidiaries, which was a crucial element of the research design of this paper.

Independent Variables

Direct and indirect R&D alliances. We collected data on R&D alliances from the Thomson SDC Platinum database by searching for all name variations of the R&D subsidiaries and firms. We assigned all R&D alliances to specific R&D subsidiaries based on the names and addresses reported in the alliance announcements. *Number of direct alliances* is measured by counting all operational R&D alliances of the focal subsidiary. *Number of indirect alliances* is measured by calculating all operational R&D alliances of the other R&D subsidiaries of the focal firm. Following prior research (e.g., Vasudeva & Anand, 2011; Grigoriou & Rothaermel. in press), we assume that R&D alliances remain operational for five years after their formation.

Knowledge overlap. To measure the *overlap in knowledge bases* between the focal R&D subsidiary and the sister R&D subsidiaries, we relied on information of the scientific disciplines in which R&D subsidiaries published in the past five years. Each publication in the Web of Science, or more specifically each journal issue in which it is published, is assigned to one or multiple discipline codes, the so-called Subject Categories (Haustein, 2012). We calculated for each R&D subsidiary per year the share of publications that were assigned to each of the 216 Subject Categories. Following Van de Vrande (2013), we used Jaffe's (1986) measure of technological proximity to calculate the extent to which the knowledge profiles of two subsidiaries are similar. This measure correlates the vector of shares in each discipline code for each subsidiary-sister combination. A value of 0 indicates that subsidiaries have completely different knowledge bases, where a value of 1 shows that subsidiaries have perfect knowledge overlap in that particular year. Subsequently, to create a measure at the level of individual R&D subsidiaries, we calculated for each R&D subsidiary the average level of knowledge overlap with its sister R&D subsidiaries that had indirect alliances.

Involvement in joint R&D projects. To examine whether the involvement in joint R&D projects facilitates the extent to which R&D subsidiaries can recombine knowledge from indirect alliances, we make a distinction between *connected indirect alliances* and *unconnected indirect alliances.* Whether two R&D subsidiaries are strongly connected is measured by the joint authorship of scientific articles. Joint authorship reflects the involvement in joint research projects and requires active knowledge exchange (Cockburn and Henderson, 1998). The existing literature has shown that co-publications are a reliable indicator for joint research projects (Cockburn & Henderson, 1998; Frenken et al., 2005; Haustein, 2012; Hicks, Isard, and Martin, 1996; Melin and Persson, 1996). In the study of Melin and Persson (1996), only five percent of the surveyed scientists reported instances of collaboration not resulting in co-authored papers. In addition, based on a survey of firms in the electronics and pharmaceutical industries, Hicks et al. (1996) found that the large majority (84-93%) of co-publications are the result of at least some sort of collaboration between individuals.

We checked whether members from two R&D subsidiaries belonging to the same MNC were listed as an author on the same scientific publication in the past five years. Accordingly, *connected indirect alliances* is calculated as the number of indirect alliances formed by sister

R&D subsidiaries with which the focal R&D subsidiary has one or more co-publications in the past five years. *Unconnected indirect alliances* is calculated as the number of indirect alliances formed by sister R&D subsidiaries with which the focal R&D subsidiary had no co-publications in the past five years. To test hypothesis 5, which examines the interaction between knowledge overlap on the one hand and connected and unconnected indirect alliances on the other hand, we create two separate knowledge overlap variables. First, the variable *knowledge overlap with connected subsidiaries* reflects the average level of knowledge overlap between the focal R&D subsidiary and subsidiaries with whom it had joint R&D projects in the past 5 years. Second, the variable *knowledge overlap with unconnected subsidiaries* is measured as the average level of knowledge overlap between the focal R&D subsidiary and subsidiaries with whom it did not have joint R&D projects in the past 5 years.

Control Variables

First, we control for characteristics of the focal R&D subsidiary. We include the variable *relative size of the subsidiary* as larger R&D subsidiaries have more access to resources and knowledge and might therefore be more efficient in their R&D activities (Minbaeva, Pedersen, Björkman, Fey, & Park, 2003). The relative size of a R&D subsidiary is measured by dividing the number of publications of the focal subsidiary by the number of publications of the firm, using a five-year lagged window. A second measure considers the *research orientation* of the R&D subsidiary. We classified publications as reporting on applied or basic research based on the journal in which they are published and the CHI journal classification scheme which classifies WoS journals in one of four research levels, in a spectrum ranging from very applied to basic research (Della Malva et al., 2015; Hicks et al., 1996). For biomedical journals, in which the sample firms publish, the four research levels are ‘clinical observation’ (level 1), ‘clinical mix' (level 2), 'clinical investigation' (level 3) and 'basic biomedical research' (level 4). The variable research orientation measures the extent to which a R&D subsidiary focuses on basic research. It is operationalized as the share of publications of a R&D subsidiary that are classified in CHI level 4, using a five year lagged window.

In addition, we include several control variables to account for the position of the focal R&D subsidiary in the MNC-network. Occupying a more central position in a network is found to increase the number of knowledge flows that one receives (Powell, Koput, & Smith-Doerr, 1996), which is likely to increase the development of new ideas. We use the *degree centrality* by counting the number of ties of the R&D subsidiary within the intra-firm network based on the number of co-publications in the past five years. Further, R&D subsidiaries that are more geographically distant from their sister R&D subsidiaries are expected to underperform since they can benefit less from intra-MNC knowledge flows (Monteiro et al., 2008). *Geographical distance* between the focal R&D subsidiary and its sister R&D subsidiaries is estimated by calculating the number of kilometers between the city locations of the focal R&D subsidiary and each of its sister R&D subsidiaries, while taking into account the surface of the earth. To compute these distances, we used the 'geodist' function in STATA (Bouquet & Birkinshaw, 2008). Subsequently, we are averaging all distances to create a subsidiary-level variable. A higher value indicates that, on average, the focal R&D subsidiary is located further away from its sister R&D subsidiaries. Moreover, we include the *number of R&D sister subsidiaries* as a measure of the size of a firm's R&D activities, which is likely to influence the scientific performance of the focal R&D subsidiary. The more sister R&D subsidiaries, the more information the R&D subsidiary is likely to receive on new developments. Moreover, competition between different R&D subsidiaries can also stimulate performance (Bouquet & Birkinshaw, 2008).

Estimation Method

Since our dependent variable is a count variable we employ a negative binomial regression model to deal with the count data characteristics of this variable as well as with the over-dispersion present in our data. Our empirical model also includes a full set of subsidiary fixed effects to account for remaining time-constant unobserved heterogeneity across R&D subsidiaries and firms. A Hausman test[2] indicated that not considering time-constant differences across firms would result in biased results. We also include year fixed effects to account for possible variations in economic conditions over time. To reduce concerns about endogeneity we include a one year time lag between the dependent and independent variables.

RESULTS

Table 1 shows the descriptive statistics and pairwise correlations of the dependent and independent variables. The correlation matrix shows relatively low correlations between the independent variables. The only two correlations above the common threshold of 0.7 are not included in the same analyses (indirect alliances and unconnected indirect alliances are highly correlated as well as knowledge overlap and unconnected knowledge overlap). The VIF values of the independent variables show no evidence of multicollinearity as all values are below the common threshold of 10, with a mean VIF value across the different models of 2.70.

Insert Tables 1 and 2 about here

Table 1 shows that R&D subsidiaries have, on average, a citation-weighted publication count of 193.80. There is substantial heterogeneity in scientific performance across the R&D subsidiaries as about 40% of the R&D subsidiaries does not receive any publications in a particular year. Moreover, from the table we observe that R&D subsidiaries have an average of 0.54 direct alliances and 19.14 indirect alliances. Direct alliances are stronger correlated with scientific performance (0.41) than indirect alliances (0.03). When we distinguish between connected and unconnected indirect alliances, we see substantial differences. The connected indirect alliances are positively correlated with scientific performance (0.25), whereas the unconnected indirect alliances are negatively correlated with scientific performance (-0.05). Knowledge overlap is found to correlate positively (0.14) with scientific performance.

To examine these observations in more depth, we conducted stepwise fixed-effect negative binomial regressions (see Table 2). Model 1 is the baseline model and only includes the control variables. We add direct alliances in model 2 and indirect alliances in model 3. Subsequently, the direct effect of knowledge overlap is included in model 4 and its interaction effect with indirect alliances in model 5. In model 6 we distinguish between connected and unconnected indirect alliances. Finally, model 7 shows their interaction with knowledge overlap.

The results of the baseline model (model 1) show that relatively large R&D subsidiaries and R&D subsidiaries which are more oriented towards basic research have, on average, a higher scientific performance. In addition, R&D subsidiaries that have more connections within the intra-firm network (e.g. high degree centrality) have a higher scientific performance. Further, R&D subsidiaries that are located at a larger geographic distance from their sister R&D subsidiaries record a lower scientific performance. Finally, we find that R&D subsidiaries which are part of a MNC network with many sister R&D subsidiaries have a lower scientific performance. A possible explanation may be that in these firms individual R&D subsidiaries get less attention and resources from the corporate headquarters.

To test hypotheses 1 and 2, we use the results of model 4. Hypothesis 1 states that the number of indirect alliances is positively related to the scientific performance of the focal R&D subsidiary. The results of model 4 in table 2 provide clear support for this hypothesis as the coefficient of indirect alliances is positive and highly significant. Subsequently hypothesis 2 proposes that the effect of indirect alliances is less outspoken than the effect of direct alliances. Looking at the results in model 4, we observe that the coefficient for direct alliances is significantly larger (Wald-test, χ_1^2= 3.33, p = 0.07) than the coefficient for indirect alliances. Hypothesis 2 is therefore supported. In a negative binomial regression model, coefficients can be interpreted as semi-elasticities. Hence, a standard deviation increase in the number of indirect alliances increases the scientific performance of a focal R&D subsidiary by 11.7%[3].

According to hypothesis 3, knowledge overlap between subsidiaries facilitates the transfer of knowledge and therefore influences the extent to which R&D subsidiaries can learn from the indirect alliances formed by their sister subsidiaries. The results of model 5 show that knowledge overlap is positively and significantly related to subsidiary scientific performance. Moreover, the interaction between indirect alliances and knowledge overlap is positive and significant, providing support for hypothesis 3. The coefficient of indirect alliances is non-significant, which shows that, in the extreme case that there is no knowledge overlap, R&D subsidiaries do not benefit from indirect alliances of their sister R&D subsidiaries. Further calculations show that for an average level of knowledge overlap, a standard deviation increase in the number of indirect alliances corresponds to an increase in scientific performance of a focal

R&D subsidiary by 7.6%. For a high level of knowledge overlap, a standard deviation increase in indirect alliances increases the scientific performance of the focal R&D subsidiary by 31%[4].

In hypothesis 4, we argue that the number of connected indirect alliances has a stronger effect on the scientific performance of a focal R&D subsidiary compared to the number of unconnected indirect alliances. In model 6, we observe that the coefficient of connected indirect alliances is significantly larger (Wald test, χ_1^2= 16.18, p = 0.000) than the coefficient of unconnected indirect alliances. These findings show that being connected to sister R&D subsidiaries that are involved in R&D alliances facilitates the extent to which a subsidiary can learn from these alliances, providing support for hypothesis 4. Further calculations, based on the coefficients of connected and unconnected indirect alliances, show that in case a R&D subsidiary has no connections to sister R&D subsidiaries that form alliances, a standard deviation increase in the number of indirect alliances increases the scientific performance with 9.7%. In the other extreme case in which a R&D subsidiary would be connected to all the sister R&D subsidiaries that form alliances, the same standard deviation increase in the number of indirect alliances would increase subsidiary performance with 25.3%.

Finally, we examine whether the effects of connected and unconnected indirect alliances are moderated differently by knowledge overlap. Model 7 presents analyses where we distinguish between two types of knowledge overlap, namely between the focal R&D subsidiary and the connected sister subsidiaries as well as between the focal R&D subsidiary and the unconnected sister subsidiaries. The interaction effect between the number of connected indirect alliances and knowledge overlap is not significant. In contrast, the interaction effect between the number of unconnected indirect alliances and knowledge overlap is positive and highly significant. Hence, we find support for hypothesis 5 that knowledge overlap has the strongest moderating effect on the relationship between the number of unconnected indirect R&D alliances and the scientific performance of a focal R&D subsidiary. Further calculations show that the effect of a one standard deviation increase in the number of unconnected indirect alliances on the scientific performance of a focal R&D subsidiary increases from 3.4% to 27.8% if knowledge overlap increases from an average to a large (e.g. mean + 2 standard deviations) value.

Next to the positive effects, our results also point to potential negative effects of unconnected indirect alliances in case that there is no knowledge overlap. More specifically, one standard deviation increase in the number of unconnected indirect alliances decreases the subsidiary scientific performance with 7.5% when there is no knowledge overlap with sister subsidiaries. This indicates that indirect alliances harm the scientific performance of subsidiaries which have no knowledge overlap and, at the same time, have no joint research projects with sister subsidiaries that form strategic alliances. In the discussion section, we elaborate on these unexpected negative effects of indirect alliances.

Robustness Checks

We have conducted a number of additional tests to check the robustness of our results. The results of these analyses are available upon request from the authors. First, although we did not expect a priori any non-linear effects of direct and indirect alliances, we have conducted an additional robustness analysis where we added the squared terms of direct and indirect alliances to model 3 (Deeds & Hill, 1996; Duysters & Lokshin, 2011). The results of these analyses provide no evidence for a non-linear relationship between direct and indirect alliances on the one hand and scientific performance of R&D subsidiaries on the other hand. Second, we have tested for a possible substitution effect between direct and indirect alliances by adding the interaction effect between direct and indirect alliances to our models. The interaction effect is found to be not significant. Finally, we include additional firm-level control variables (e.g. total number of sales and the R&D intensity of the firm; see for a similar approach: Almeida & Phene, 2004; Berry, 2013) to account for remaining time varying differences across firms that are not be fully captured by the subsidiary fixed effects. The results are robust to the inclusion of these variables. In sum, we conclude that our results are stable to a number of robustness checks.

DISCUSSION AND IMPLICATIONS

Whereas the alliance portfolio literature already points to the distinction between single- and portfolio-level alliance knowledge recombination (Wassmer & Dussauge, 2011a), we relied on insights from social network theory to make an additional distinction between direct and indirect alliance knowledge recombination. Doing so, our empirical findings provide strong support that, next to directly benefiting from alliances that are formed by the focal subsidiary unit, being part of an internal network provides indirect knowledge recombination opportunities as subsidiaries can also benefit from alliances that are formed by sister units within the same MNC. At the same time, we point to important internal boundary conditions that influence the extent to which such indirect knowledge recombination can manifest itself. Whereas prior alliance portfolio research has focused on the differences between firms in creating value from alliances, our findings demonstrate that we also need to understand within-firm differences, and examine why subsidiaries differ in terms of their ability to realize benefits from alliance portfolios of the MNC to which they belong. In this way, our study contributes to the alliance portfolio literature by developing a more in-depth theoretical understanding of how external knowledge is recombined and used within the firm.

Our findings also have implications for the emerging body of research on the interactions between external and internal knowledge networks. Recently, some studies have started exploring how the internal knowledge network (i.e. the structure of the internal co-inventor network) influences the ability of firms to reap benefits from their external knowledge sourcing networks. Grigoriou and Rothaermel (in press), for instance, observed that particular co-inventor network characteristics – i.e. average path length and degree of clustering - negatively moderate the relationship between the number of exploration alliances and pharmaceutical incumbent's ability to develop knowledge in the biotech paradigm. In addition, Laursen et al. (2015) found that the diversity, average tie strength, and density of the internal inventor network of established pharmaceutical firms influence the speed of recombining in-licensed knowledge. Although these studies provide important insights, they ignore that external sourcing activities can be widely dispersed across different organizational entities of the focal firm. This is definitely the case in the particular setting of pharmaceutical firms that typically have globally distributed R&D activities where individual R&D subsidiaries can engage in alliance activities (Bos et al., 2014). In other words, whereas prior studies fully acknowledge the importance of considering the dispersion of, and connections between, inventors within the firm, they ignore the potential dispersion of external knowledge sourcing activities within the focal firm. In this paper, we addressed this latter issue by shifting the level of analysis from the firm-level to the subsidiary-level. In this way, we were able to theorize on and empirically demonstrate that subsidiaries can not only rely on their direct alliance partners for external knowledge recombination activities, but can also rely on indirect alliance partners (i.e. the alliance partners of sister subsidiaries).

At the same time, the ability to benefit from indirect alliances is determined by the nature of the internal knowledge network. R&D subsidiaries that have a knowledge base that overlaps with their sister subsidiaries, or which engage in joint R&D projects, are found to benefit the most from indirect alliances. At the same time, we observe that, when R&D subsidiaries lack knowledge overlap and joint projects with their sister R&D subsidiaries, these isolated subsidiaries experience a negative effect of the number of indirect alliances on their scientific performance. Attention-based view scholars (Hung, 2005; Ocasio, 2011) have referred to external network ties as attention structures that might influence the allocation of attention of organizational units. Following this logic, we argue that indirect alliances can function as external actors that attract attention of focal R&D subsidiaries. For instance, an indirect alliance might signal a new scientific approach that the focal subsidiary regards as an opportunity for new experiments. However, our results indicate that, when this focal subsidiary lacks knowledge overlap or joint projects with the sister subsidiary that engaged in the alliance, it is unlikely to successfully experiment with the new scientific approach of the indirect alliance partner. In such a case, the indirect alliance mainly functions as a distraction from other R&D activities, drawing attention to external opportunities for which the focal subsidiary lacks the necessary absorptive capacity to effectively use them. In sum, these latter findings suggest that, for isolated R&D subsidiaries, indirect alliances merely function as distracting attention structures, negatively influencing the effectiveness of the focal subsidiary’s scientific efforts. Together, these insights substantially enrich our understanding of the potential complementarities and trade-offs between external knowledge sources and firms’ internal knowledge base (Cassiman & Veugelers, 2006; Cohen & Levinthal, 1990).

Managerial Implications

Our findings have important implications for managers of MNCs. On the subsidiary level, our findings strongly suggest that subsidiary managers, when searching for new external knowledge recombination opportunities, should not only consider their direct alliance partners, but also take into account the alliance partners of their sister subsidiaries. Moreover, our results indicate that alliance partners from two types of subsidiaries are especially relevant to consider. A first option are sister subsidiaries with whom the focal subsidiary has a history of extensive collaboration. A second option is to consider the alliance partners of subsidiaries with whom no history of collaboration is established but that have a largely overlapping knowledge base.

On the firm level, our findings reaffirm the importance of fostering cooperation between subsidiaries. However, whereas prior research (e.g. Gupta & Govindarajan, 1994; Minbaeva et al., 2003) mainly emphasized the advantages of intensive cooperation among subsidiaries to maximize knowledge spillovers from the MNCs internal knowledge pool, we stress that such cooperation can also trigger additional external knowledge recombination benefits as it increases the ability of subsidiaries to reap benefits from indirect alliance partners. Further, our findings inform firm managers on the organization of multi-unit innovation networks. More specifically, we find that in order to widely benefit from knowledge recombination within an alliance portfolio of a MNC, it is important that different subsidiaries share a partly overlapping knowledge base. This requires that firms are willing to give up some scale economies of having specialized subsidiaries by duplicating some scientific expertise across different subsidiaries (Zander, 1998).

Limitations and suggestions for future research

This study has several limitations, which also provide interesting avenues for future research. First, the setting of our study is limited to the pharmaceutical industry. Although we expect our findings to hold for multinational firms in R&D-intensive industries in general, future research needs to be conducted to examine their generalizability. Second, whereas previous research mainly used patents to operationalize knowledge networks, we have used scientific publications. While scientific publications were the best option in our case as we focused on geographically dispersed subsidiaries, requiring in-depth information on the location of subsidiaries, more research is necessary to identify the differences and similarities between both data sources. Third, we focus in this study on R&D alliances. Finally, future research could investigate whether subsidiaries use different management practices to learn from indirect alliances. In this way, we could develop deeper insights in how subsidiaries deal with different challenges, which might help us to identify best practices to maximize the ability to reap indirect alliance knowledge recombination opportunities.

CONCLUSION

In this study, we examine the subsidiary-level implications of alliance portfolios that are formed by firms. Relying on insights from social network theory, we distinguish between direct (e.g. formed by the focal subsidiary) and indirect alliances (e.g. formed by its sister subsidiaries). Our empirical analysis provides strong support that, next to direct alliances, indirect alliances influence subsidiary scientific performance. In addition, we complement social network theory with KBV-arguments to show that the effect of indirect alliances is contingent on a number of conditions - being knowledge overlap or the involvement in R&D projects. Differentiating between the implications of direct and indirect alliances and shifting the analysis to the subsidiary-level, our study reveals new insights into the value creation and destruction consequences of alliance portfolios for MNCs and their subsidiaries.

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FOOTNOTES

[1] As a robustness check, we linked all patents of the firm Abbott to the identified R&D subsidiaries. The number of publication citations and patent citations are highly correlated (r = 0.85). This indicates that we can assume that both measures are likely to provide similar results.

[2] A Hausman test was conducted using model 5 to compare the coefficients from the fixed effects model with the random effects model. The Chi-square test-statistic is highly significant (χ^2_{16}= 197.05, p = 0.00), suggesting that the random effects estimator is inconsistent. We therefore select the fixed effects model.

[3] This number is calculated by multiplying 0.6% and 19.5 (standard deviation of indirect alliances).

[4] A high level of knowledge overlap is defined as the mean value + two standard deviations. The above calculations follow from estimating above models with different levels of centering for knowledge overlap.

TABLES

Table 1:

Summary Statistics and Correlations

	Mean	Std. dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Scientific performance t+1 (1)	193.80	1013.60	1											
Relative size subsidiary (2)	0.07	0.19	0.26*	1										
Research orientation subsidiary (3)	0.20	0.30	0.12*	0.23*	1									
Degree centrality (4)	1.13	2.51	0.57*	0.16*	0.13*	1								
Geographical distance (5)	5486.35	2693.76	-0.01	-0.21*	-0.11*	-0.05*	1							
Number of sister subsidiaries (6)	46.51	37.60	0.03*	-0.34*	-0.10*	0.18*	0.21*	1						
Direct alliances (7)	0.54	2.39	0.41*	0.35*	0.09*	0.33*	-0.05*	-0.04*	1					
Indirect alliances (8)	19.14	19.52	0.03*	-0.29*	-0.08*	0.09*	0.19*	0.71*	-0.06*	1				
Connected indirect alliances (9)	2.52	6.22	0.25*	-0.04*	0.06*	0.46*	0.03*	0.21*	0.04*	0.28*	1			
Unconnected indirect alliances (10)	16.62	18.74	-0.05*	-0.29*	-0.10*	-0.06*	0.19*	0.67*	-0.07*	0.95*	-0.04*	1		
Knowledge overlap (11)	0.25	0.23	0.14*	-0.06*	0.10*	0.30*	-0.02*	-0.03*	0.03*	0.02*	0.24*	-0.05*	1	
Knowledge overlap with connected subsidiaries (12)	0.12	0.25	0.25*	0.01	0.12*	0.52*	-0.01	0.10*	0.08*	0.10*	0.63*	-0.11*	0.51*	1
Knowledge overlap with unconnected subsidiaries (13)	0.21	0.21	0.06*	-0.11*	0.04*	0.14*	0.01	0.08*	0.02*	0.11*	0.03*	0.11*	0.77*	0.07*

* p < .05

Table 2: Indirect Alliances and the Scientific Performance of R&D Subsidiaries [a]

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Relative size subsidiary	0.853***	0.816***	0.859***	1.209***	1.162***	1.183***	1.143***
	(0.085)	(0.086)	(0.087)	(0.089)	(0.089)	(0.088)	(0.088)
Research orientation subsidiary	0.157**	0.160**	0.170**	0.074	0.065	0.076	0.066
	(0.055)	(0.055)	(0.055)	(0.057)	(0.057)	(0.057)	(0.057)
Degree centrality	0.159***	0.157***	0.159***	0.134***	0.130***	0.118***	0.119***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Geographical distance	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of sister subsidiaries	-0.002***	-0.002***	-0.004***	-0.002**	-0.002*	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Direct alliances		0.008*	0.010*	0.013***	0.012**	0.013***	0.012**
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Indirect alliances			0.007***	0.006***	-0.002		
			(0.001)	(0.001)	(0.002)		
Knowledge overlap				1.314***	1.012***		
				(0.066)	(0.078)		
Indirect alliances * Knowledge overlap					0.025***		
					(0.003)		
Connected indirect alliances						0.013***	0.017***
						(0.002)	(0.005)
Knowledge overlap with connected subsidiaries						1.050***	1.000***
						(0.061)	(0.062)
Connected alliances * Knowledge overlap with connected subsidiaries							-0.008
							(0.007)
Unconnected indirect alliances						0.005***	-0.004*
						(0.001)	(0.002)
Knowledge overlap with unconnected subsidiaries						0.925***	0.636***
						(0.064)	(0.076)
Unconnected alliances * Knowledge overlap with unconnected subsidiaries							0.030***
							(0.004)
Constant	-0.733***	-0.735***	-0.844***	-1.245***	-1.161***	-1.182***	-1.101***
	(0.061)	(0.061)	(0.064)	(0.068)	(0.068)	(0.067)	(0.067)
AIC	58169.35	58166.50	58126.76	57745.96	57689.07	57584.11	57350.85
BIC	58272.61	58277.13	58244.76	57871.34	57821.82	57724.24	57685.74
LR Test Model 2 vs. Model 1		4.85*					
LR Test Model 3 vs. Model 2			41.74***				
LR Test Model 4 vs. Model 3				382.80***			
LR Test Model 5 vs. Model 4					58.89***		

LR Test Model 6 vs. Model 5	106.96***	
LR Test Model 7 vs. Model 6		57.26***

[a] Fixed effects negative binomial regression with robust standard errors in parentheses. ***, **, *, + indicates significance at the 0.1%, 1%, 5%, and 10% level. All regressions include a full set of subsidiary and year fixed effects which are not reported for brevity. The total number of observations is 11794 with 1961 unique subsidiaries.

FIGURES

Figure 1.

Two Types of Alliance Resource Recombination, namely 1 on the single alliance-level and 2 on the alliance portfolio-level (Figure from Wassmer and Dussauge, 2011a).

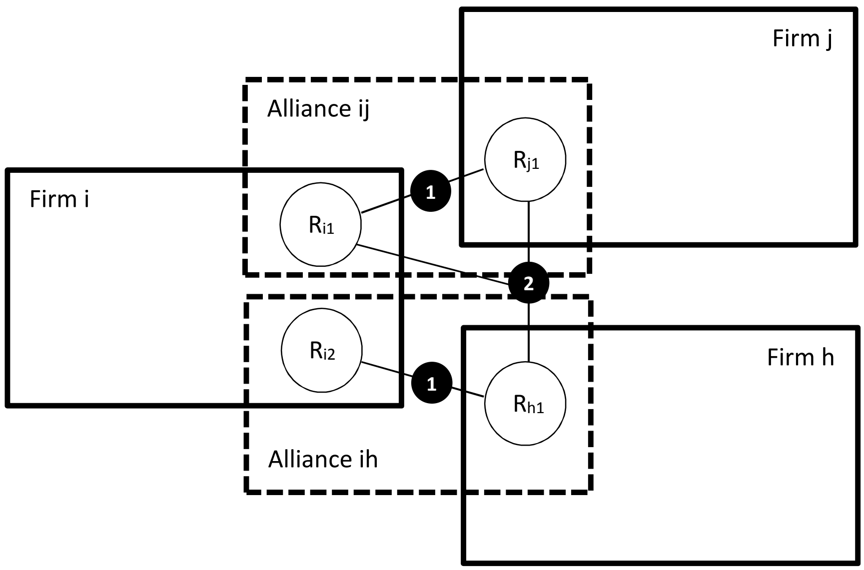
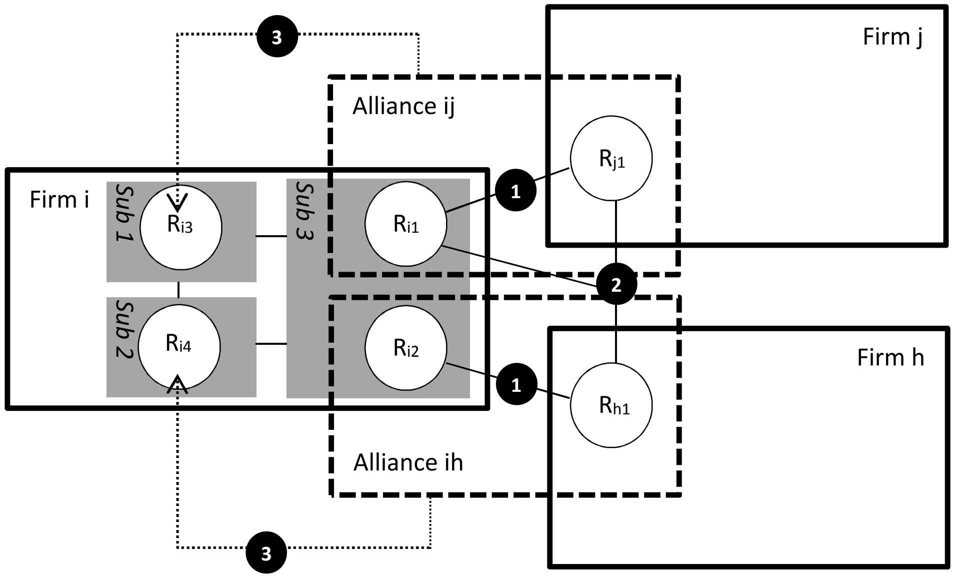


Figure 2.

Different Types of Alliance Knowledge Recombination (Adapted figure from Wassmer and Dussauge, 2011a).



Alliance knowledge recombination	Single alliance-level	Alliance portfolio-level
Direct	1	2
Indirect	3	