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Open Innovation and R&D Alliances: The Double-Edge Sword of Technological Breadth

Abstract

This paper studies opportunism in biopharma R&D alliances by highlighting the role of each partner's technological breadth in the dynamics that determine the size of the alliances. We posit that, on one hand, the breadth of technological resources of the upstream R&D partner (typically a dedicated biotechnology firm) enables it to divert resources from the alliance to unrelated projects at the expense of the downstream financing partner (typically a "Big Pharma" company). On the other hand, the breadth of technological resources of this downstream partner enables it to better monitor the opportunistic behavior of its R&D partner. Thus, we hypothesize that the R&D partners with broad technological knowledge are more likely to be at a disadvantage and may end up receiving smaller amounts upfront in the alliance, while the downstream partners with broad technological knowledge are more likely to pay larger amounts upfront. Furthermore, we hypothesize that partner familiarity strengthens (weakens) the positive (negative) relationship between downstream partner's (R&D partner's) technological breadth and the size of the alliance. We test these hypotheses in a sample of 178 R&D alliances formed between 2006 and 2015. We find the main effects of technological breadth are significant for both the R&D and downstream partners. However, with respect to the moderation effects, familiarity between partners only weakens the negative impact of technological breadth of the R&D partner but does not significantly strengthen the positive impact of technological breadth of the downstream firm. We discuss the implications of our findings for theory and practice.

Keywords: R&D alliance, Open Innovation, Opportunism, Technological Breadth, Biopharma

1. Introduction

Open Innovation (OI) is defined as "a distributed innovation process based on purposefully managed knowledge flows across organizational boundaries, using pecuniary and non-pecuniary mechanisms in line with the organization's business model" (Chesbrough and Bogers, 2014, p. 12). Inter-organizational collaboration practices such as research and development (R&D) alliances, which are prevalent in industries characterized by rapid technological change, have been widely studied through an "open innovation" lens (Bagherzadeh et al., 2019; Bogers, 2011; Bogers et al., 2017; Frankort and Hagedoorn, 2022; Majchrzaket al., 2015). For example, inter-organizational collaborations in the biopharmaceutical industry, where large pharma companies form R&D alliances with dedicated biotech firms, have been studied by OI scholars (e.g., Nigro et al., 2014; Xia and Roper, 2016). R&D alliances in the biopharmaceutical industry are illustrative examples of open innovation practices, where the pharma firms provide financing and downstream capabilities in exchange for accessing the biotech firm's upstream research capabilities (Rothaermel, 2001).

However, research has shown that these types of alliances also pose thorny agency hazards, which can impede the flow of knowledge between the alliance's partners and therefore the alliance less valuable (Argyres et al., 2020; Gambardella and Panico, 2014; Oxley and Sampson, 2004). Specifically, the downstream firm (typically a big pharma company) may be concerned about two related issues: the R&D firm (typically a dedicated biotech firm) diverting resources from the intended project to unrelated ones (Holmström and Milgrom, 1991), as well as its own lack of capabilities to monitor the R&D firm's resource allocation adequately (Robinson and Stuart, 2007). While other researchers have studied governance mechanisms that help mitigate such moral hazards (e.g., Morgan et al., 2018; Singh and Gaur, 2021; Zhao et al., 2021), we know little about how and whether these agency hazards also influence what the large downstream firm is willing to pay to the upstream R&D firm to form and sustain the alliance.

In this paper, we posit that the breadth of technological resources of the R&D partner provides it the means to divert resources across to unrelated projects at the expense of the large downstream partner. However, the breadth of technological resources of the downstream partner acts as a counter and enables it to better monitor such opportunistic behavior of its R&D partner. Thus, we argue that the potential for opportunistic behavior from the R&D partners with broad technological knowledge puts them at a disadvantage and causes them to end up with smaller alliances (in financial terms), while downstream partners with broad technological knowledge can form larger alliances because of their oversight capabilities. The opposing directions of the impact of a partner's technological breadth are due to the information asymmetry that drives the fear of opportunistic behavior between the partners (e.g., Akerlof, 1978; Corsi et al., 2021; Heide, 2003; Steinle et al., 2014). Finally, we argue that when the two partners have had previous alliances with each other, they are more familiar with each other's businesses and practices leading to greater trust (Gopalakrishnan et al., 2008; Dunne et al., 2009). We use familiarity as a moderator and argue that it will attenuate the negative impact of the R&D firm's breath and accentuate the positive impact of the downstream company's breadth of technological knowledge on the amount of upfront payment in the alliance.

Using a sample of 178 R&D alliances formed between 2006 and 2015, we test and confirm our main effect hypotheses regarding the association between technological breadth and upfront payment (which is sometimes called alliance size), the latter being an indicator of the downstream partner's willingness to pay in forming the alliance. Numerous contractual terms with contingent payments are at play to align the incentives of the two partners and mitigate moral hazards in these alliance agreements. However, as we are interested in capturing the downstream partner's fear of the R&D partner's opportunistic behavior at the time of the alliance formation, we only consider the amount paid upfront upon signing the alliance agreement[1] (Farazi et al., 2016; Gopalakrishnan et al., 2008; Tyebjee & Hardin, 2004).

Our research contributes to the literature on R&D alliances and OI in several ways: First, while earlier alliance research focused mostly on firm-level characteristics of one of the alliance partners (e.g., Chang, 2003; Dunne et al., 2009), recent research has shown the benefits of using a dyadic approach examining the joint impact of both partner characteristics on alliance outcomes (e.g., Mindruta, 2013; Mindruta et al., 2016). Second, despite the importance of alliance size in determining the outcome of technology alliances, past research has not extensively studied the link between technological resources and the financial size of the alliance at the dyadic level. Third, while past research has studied the issue of opportunistic behavior by the larger partner in an alliance, little attention has been paid to the potential of such moral hazard due to the actions of the smaller partner. Our contribution therefore speaks to the growing literature on "the dark side of open innovation" (Chaudhary et al., 2022; Purdy et al., 2023; Stefan et al., 2022).

The next section provides the theoretical foundation for this study and presents the three hypotheses. Section 2 examines the theoretical background and hypotheses; section 3 describes the research methodology while section 4 presents the results of our study. Section 5 concludes the paper by discussing the findings as well as outlining our study's theoretical contributions and managerial implications.

2. Theoretical background and hypotheses

[1] The term "alliance size" throughout this paper refers only to the upfront payment by the downstream partner, typically to finance the R&D partner's drug discovery and development activities or to in-license a technology or molecule from this partner. In contrast, "total alliance size" is the total possible value of the alliance transaction which the downstream partner has agreed to pay to the R&D firm at different stages throughout the alliance's life.

Past research on R&D alliances has generally focused on the factors that impact alliance formation between alliance partners (Mindruta et al., 2016; Rothaermel and Boeker 2008; Yayavaram et al., 2018; Zhang 2016) as well as alliance performance measures such as innovation, alliance size, knowledge growth, technological advancement, and competitive advantage (Carnabuci and Operti, 2013; Sabidussi et al., 2017; Zhang et al., 2022). In many of these alliances, we have the R&D firm on the one side, which tends to be smaller and more skilled in upstream activities such as research and product development (Hoang and Rothaermel, 2010). On the other side, there are the downstream, typically large firms that contribute a variety of resources beyond financial (e.g., manufacturing, marketing, distribution, and legal expertise) to the alliance (Cherbib et al., 2021; Kim, 2011).

Following previous research that has viewed technological alliances from a knowledge-based lens (for example, Santoro & Bierly, 2006), we believe that the R&D firms use their knowledge-based resources to bargain for additional financial capital (as various parts of the total alliance size) from the downstream partners. For example, in technologically advanced sectors such as biopharma, the most novel technologies are often developed by small firms which leverage this capability as an opportunity to tap the deep pockets of the larger pharmaceutical firms (Gopalakrishnan et al., 2008; Rothaermel and Deeds 2004). In this section, we elaborate on how in addition to the size of the partners, the breadth of technological knowledge of partners impacts the upfront payment in the alliance.

2.1 Alliance size and information asymmetry

Past research has found large incumbents with more resources are likely to enter alliances because they can reap advantages by more efficiently utilizing their downstream capabilities (Park et al., 2002). These downstream firms commit several fixed and contingent payments to the R&D partners in the alliance contract. The total alliance size (a.k.a total bio-dollars) is the sum of all such possible payments, and it has implications beyond the financing of the alliance project. For a young technology firm, the total alliance size signals credibility to the outside investors that a large downstream firm, usually well-known in the marketplace, has agreed to provide such funds. It is therefore expected that an R&D firm will try to sign an alliance with as large a size as possible for financing to enhance their reputation.

The downstream firm views the discretionary power wielded by the biotechnology R&D firm as a potential source of opportunism. Because the R&D firm usually works closely on the R&D project it has greater knowledge about the underlying technology and its prospects than any potential downstream partners. With the presence of information asymmetries, the R&D firm could direct the resources towards purposes other than what had been mutually agreed upon in the alliance (Lerner and Malmendier, 2010), a type of moral hazard known as the agent's multitasking (Holmstrom & Milgrom, 1991). There are subtle ways to channel resources in this way. For instance, R&D firms may allocate key human resources in a way that is not in the best interest of the alliance overall, but in the interest of some side-project or experimentation (Farazi et al., 2024; Kim, 2011).

2.2 The relationship between partners' technological breadth and upfront payment in the alliance

Drawing on the knowledge-based view of alliances, we examine the role of both firms' current knowledge base on the potential size of alliances. Past research suggests that a rich knowledge base results in a strong absorptive capacity that better enables a firm to evaluate and assimilate the knowledge of its partners (Cohen and Levinthal, 1990; Chen, 2004).

Technological breadth refers to the scope of the firm's technological knowledge base, usually measured by the number of different technological niches in which a firm operates. Firms with broad technological knowledge are familiar with several knowledge domains and thus, can pursue more paths in new areas of business (Kauffman et al., 2000). To sense and develop new business opportunities, firms need to constantly scan and search across technologies and markets, especially in distant territories beyond their existing knowledge base (Teece, 2007).

While the bargaining power of the smaller partner, i.e., the R&D firm, increases with the value of its knowledge-based resources, the downstream partner might be concerned about the "breadth" of such knowledge-based resources across multiple technologies. In industries such as biopharma, where technological knowledge tends to be tacit and rapidly evolving, it is reasonable to expect that the larger downstream company may not possess the full range of related expertise in any given therapeutic area where it is developing a drug to bring to market. Therefore, they enter alliances with smaller biotech firms: For example, the pharmaceutical giant Pfizer was not an expert in the mRNA drug development technology, and they entered into a deal with BioNTech (a smaller company dedicated to this cutting-edge technology) and the result of this downstream firm-R&D firm partnership (big pharma and dedicated biotech firms partnership) was a Covid-19 vaccine that proved effective in controlling the recent pandemic[2].

Larger pharmaceutical firms often look for focused biotechnology firms that have concentrated talent and resources in potentially promising technological and therapeutic areas. The breadth of knowledge, therefore, may not be a virtue that is sought after in the smaller technology firm (Zhang & Baden-Fuller, 2010). In fact, the breadth of knowledge may raise concerns in the downstream partner, of a possible moral hazard where the smaller firm can raise funds through an alliance with the larger firm and use some of the funds on projects outside the agreed scope of the alliance. Therefore, it is conceivable that the smaller firm can behave opportunistically in the use of alliance funds. Broad knowledge enables the smaller firm to recombine resources in ways that are not easily discernible to the larger partner and invest

[2] From Pfizer website (April 2022)

alliance resources in the development of other projects at the expense of the downstream partner's project (Carnabuci & Operti, 2013).

Past research has also found that technological knowledge breadth positively influences a firm's ability to find and form relationships with new partners (Zhang et al., 2007). For broad R&D firms, the costs and risks involved in reconfiguring resources to form other alliances with new partners are relatively low, because they already possess relevant human capital or equipment that could be used in new projects and hence alliance specific investments are reduced (Zhang, 2016). Moreover, firms with broad knowledge can learn fast, as their absorptive capacity enables them to build linkages between new and existing knowledge (Hamel, 1991).

Taken together, all of this means that broad R&D firms can afford to research into new technological knowledge with new partners. This ability translates into fear in the downstream partners who prefer to have greater control over the smaller R&D firm's technology trajectory to reap the maximum market benefits. The fact that the broad R&D partner is capable of rapidly learning from the "big pharma" partner and could potentially enter alliances with a rival pharmaceutical corporation can be unsettling to the downstream partner (Farazi et al., 2024). Therefore, while the R&D firm may be able to identify appropriate partners, they cannot maximize the upfront payment in the alliance because the downstream partner discounts the value of their knowledge due to the possibilities for opportunism. This results in a discount being applied on the financial appraisal of the alliance which tends to be smaller for the R&D firm. Therefore, we posit:

Hypothesis 1. *In biopharma alliances, the breadth of technological knowledge possessed by the R&D partner is negatively related to the upfront payment.*

Thus far, we have examined the breadth of technological knowledge in the R&D partner. However, the downstream partner's breadth of technological knowledge can also be an important determinant of the upfront payment: While opportunistic behavior is theoretically present in all downstream partner and R&D firm settings, it is usually the R&D partner that tends to have more private information (e.g. Akerlof, 1978; Capron & Shen, 2007). In our research context of biopharma alliances, the greater the downstream partner's breadth of knowledge across several technological or therapeutic areas, the better its oversight capabilities. This is because the downstream partner is not only familiar with the technology in question but also with areas outside the scope of the alliance (where the R&D partner might or might not have expertise). The broad technological knowledge of the downstream partner can serve as a deterrent for the R&D firm to behave opportunistically because the R&D firm is aware that the downstream partner is likely to be able to keep track of potential deviations from the agreed-upon technological trajectory.

There are other reasons why the broad downstream partner firms are likely to commit to larger amounts of financial capital in an alliance with an R&D firm. Broad technological knowledge provides the downstream partner with more flexibility to explore new technological areas by forming R&D alliances. This is because the broad knowledge base enables the firm to monitor changes in technology and recognize potential new projects (Arora & Gambardella, 1990). Also, a "broad" downstream partner has a strong capability to integrate and assimilate partners' knowledge into their existing knowledge base. In the example of the collaboration that led to the Covid-19 vaccine, Pfizer had a broad knowledge base which enabled the firm to monitor opportunities for forming alliances other than the one with BioNTech. This is an option that Pfizer would like to keep for itself, but not for its R&D partner. Also, if Pfizer had learned of other cutting-edge knowledge on mRNA therapeutics possessed by BioNTech, its broad knowledge base would give it an edge in absorbing partner's knowledge (including tacit) by categorizing new knowledge according to the ways prior knowledge is organized (Zhang, 2016).

For these reasons, when the downstream partner has a broad knowledge base it has more incentives to invest in alliances while it also has less fear of opportunistic behavior by the R&D firm and has a lower tendency to apply a discount on the perceived value of the alliance:

Hypothesis 2. *In biopharma alliances, the breadth of technological knowledge possessed by the downstream partner is positively related to the upfront payment.*

2.3. The role of partner familiarity as a moderator

The OI (open innovation) literature argues that the tension between knowledge sharing and opportunism in R&D alliances can be managed either through knowledge characteristics or through relational mechanisms (Bogers, 2011). Familiarity is an important relational mechanism that impacts alliance outcomes (Gopalakrishnan et al., 2008; Hoang & Rothaermel, 2005) and in this paper, we examine the role of familiarity between alliance partners as a moderator in the relationship between breadth of alliance of both partners and upfront payment received by the R&D partner. Familiarity between alliance partners means the partners carry some knowledge about each other that has been gained through previous direct contacts. The experience of partnering with each other gives the two firms a better understanding of each other's routines and work behaviors and leads to a more efficient collaboration (Carnabuci & Operti, 2013, Gopalakrishnan et al., 2008). Moreover, the firsthand knowledge and experience that partners gain when working together builds trust between them and leads to less fear of partner’s opportunistic behavior should they choose to enter an alliance with each other again (Ahuja, 2000) and better probability of realization of alliance outcomes.

Bogers (2011) found that in an open innovation context, there is a “layered collaboration scheme” with two types of members –“inner” and “outer” members that can be alliance partners; knowledge and other resources are shared differentially in a more open or closed way with these two types of members. Therefore, alliance partners that are more familiar are likely to be the inner members and less familiar partners will be in the outer members in R&D alliances. Familiarity builds trust, and trust operates differentially for the R&D partner and the downstream partner and affords different benefits to each.

On the one hand, familiarity reduces the fear of opportunistic behavior by the R&D partner since a familiar partner is more likely to be an inner member. Therefore, it is expected to help mitigate the downstream partner's concerns about the negative consequences of the breadth of technological resources of the R&D firm. If the two partners are entering into an alliance as a repeated tie, this implies that the previous collaboration has been successful in terms of building trust between the two partners (Gopalakrishnan et al., 2008). In this situation, there would be less fear of the R&D partner following a hidden agenda by diverting resources into projects unrelated to the funded alliance project.

On the other hand, in the case of downstream partners, familiarity allows them to allocate all the resources to the core activities of the alliance rather than spending time and other resources to monitor the R&D partner's behavior. Additionally, when the downstream partner has greater knowledge about the routines and behavior of the R&D partners, they are more proactive about forming alliances with them (Vlaisavljevic et al., 2021) as they are likely to trust them and are likely to compensate them more. The downstream partner believes that they are more able to use a collaborative IP strategy Grimaldi et al,, 2021) with a familiar R&D partner. The collaborative IP strategy allows a certain amount of conscious and selective revealing of information from the breadth of knowledge of the R&D partner. The downstream partner therefore may expect to get purposive knowledge spillovers from its R&D partner (Henkel et al., 2014) and their breadth of knowledge can help take advantage of it. Therefore, we hypothesize:

Hypothesis 3a. *In biopharma alliances, familiarity between the partners weakens the negative effect of the breadth of the R&D firm's knowledge on the upfront payment.*

Hypothesis 3b. *In biopharma alliances, familiarity between partners strengthens the positive effect of the breadth of the downstream partner's knowledge on the upfront payment.*

Figure 1 summarizes the conceptual model of this study.

Insert Figure 1 here

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3. **Methods**

3.1. **Data**

The data for this study came from Cortellis (formerly known as Recap) published by Clarivate Analytics. This dataset specializes in intellectual property data in the healthcare sector. Cortellis collates the data on alliances from several public sources, including the SEC filings of companies. The Recap database is representative of biopharmaceutical alliances as demonstrated by numerous studies in the areas of management, finance, and economics (Schilling, 2009; Adegbesan and Higgins 2011; Lerner, Shane, and Tsai 2003; Reuer and Devarakonda 2015).

For this study, we started with all the 817 alliances reported in the Cortellis database for the ten-year period from 2006-2015 for which financial data on alliance size was available. We then used both USPTO and Derwent Innovation Index to collect data on the firms' patents and their underlying technology classes. We matched the data from both sources to include as many firms as possible. Finally, we merged the firm's financial data from Compustat. We excluded deals that were not technology alliances (e.g., an asset purchase or loan). The final sample comprised 178 alliances that were formed from 2006 to 2015, with a biotechnology company being the R&D firm and a larger pharmaceutical firm being the downstream partner. The final sample size is relatively small due to merging several data sources and having to drop observations that had missing data from (at least) one of the sources. To ensure that the sample was not biased, we checked the distribution of lnSize (natural logarithm of upfront payment in the alliance) in our final sample of

178 alliances and compared it with the distribution among the dropped 660 alliances (817-178= 639 alliances). The two samples have similar distributions, suggesting that the upfront payments paid for the alliances in the final sample were not systematically different from those in the original sample.

3.2. Measures

Dependent Variable. *Upfront payment in the alliance* is the amount in US dollars that the downstream partners paid to the R&D partner on signing the alliance. This is part of the so-called "total bio-dollars"[3] which is the sum of all the maximum "possible" payments that the downstream partner agrees to pay to the R&D firm at different stages throughout the life of the alliance. According to Cortellis, the components of "total bio-dollars" include upfront cash and equity payments, milestone (including milestone sales) payments, loans, and contingent equity investments. As milestone payments are only paid after meeting previously agreed milestones in the contract, this part of the total bio-dollars is less suspectable to the moral hazards discussed above. For example, Incyte signed a partnership contract with Syros Pharmaceuticals in January 2018, and the companies agreed to work together on developing potential treatments for myeloproliferative neoplasms. Syros received $10 million upfront and, Incyte agreed to pay $54 million for target selection and option exercise fees plus $115 million in other milestone payments. However, in August 2023, Incyte ended the five-year collaboration with Syros Pharmaceuticals after rejecting all seven targets identified for myeloproliferative neoplasms by Syros for further development. Since Incyte did not select any of the targets, none of those milestones have or will

[3] Total alliance size or deal size is a number often referred to as the "bio-dollars" in business jargon. It is, however, a virtual figure and, only very seldom does the full alliance size amount get realized, as products do not often succeed by hitting all sales milestone thresholds. This figure is, however, important both in terms of the R&D firm's financing as well as signaling the quality of the R&D firm to possible future investors (Janney and Folta, 2003, 2006).

be paid out[4]. While our dependent variable is only the upfront cash, we control for the existence of equity payments, royalties and sales milestones.

Independent Variables: *Breadth of technological knowledge* is the total number of technology classes, as defined by the USPTO, where a firm (whether R&D or downstream partner) was granted patents in the past 5 years leading up to the alliance.

Familiarity: This is a dummy variable that controls whether the alliance represents a repeated tie between the two partners, or whether the two partners are new to each other. The former was coded 1 and the latter 0. Past research has found the familiarity of two partners influences alliance outcomes, including upfront payment in the alliance (Gopalakrishnan et al., 2008; Zhang, 2016).

Control Variables: We controlled for several variables that can affect the agreed upfront payment in an alliance. The first three are dummy variables to control for other components of the total alliance size, namely *Equity* (equals 1 if the alliance involved the downstream partner taking an equity stake in the R&D firm), *Royalty* (if the alliance involved royalty payments), and *SalesMilestone* (if the alliance involved milestone payments to the R&D firm if drug sales hit certain targets). Moreover, we control for firm size and firm's depth of technological knowledge:

Firm size: measured by the total assets of the firm (whether it is the R&D firm or the downstream partner) at the time of alliance formation, in million dollars. Research has found a firm's size to impact its bargaining power in alliance negotiations (Aghion and Tirole, 1994). Also, it might be that larger downstream firms have deeper pockets and tend to invest more in alliances.

Depth of technological knowledge: This is the maximum number of patents in any one technology class, as defined by the USPTO, in which the firm was granted patents in the past 5 years leading up to the alliance. This measure captures the depth of technical expertise in one area (George et

[4] https://www.fiercebiotech.com/biotech/incyte-drops-syros-blood-cancer-partnership-two-months-after-pfizer-does-same-sickle-cell

al., 2008). We follow earlier research that assumes firms can possess extensive technological knowledge breadth, depth, both, and, or neither (e.g., Farazi et al., 2019; Zhu et al., 2021). While our study focused on how the breadth of knowledge impacts upfront payment in the alliance, we control for knowledge depth because it is a relevant dimension of a firm's structure that is found to impact alliance outcomes (Zhang & Baden-Fuller, 2010).

4. Estimation Method

As our dependent variable, upfront payment in the alliance is a continuous variable, we estimated all models using an ordinary least squares (OLS) regression. All models include a set of dummies for the year to account for potential time trends affecting alliance activities within the biopharmaceutical industry. To test our hypotheses, we estimated the following model:

$$Upfront\ Payment = \alpha + \beta 1.Equity + \beta 2\ .Royalty + \beta 3\ .SalesMilestone + \beta 4.R\&Dfirm\_size + \beta 5.DSPartner\_size + + \beta 6.R\&Dfirm\_depth + \beta 7.DSPartner\_depth + \beta 8.R\&Dfirm\_breadth + \beta 9.DSPartner\_breadth + \beta 10.Familiarity + \beta 11.R\&Dfirm\_breadth \times Familiarity + \beta 12.DSPartner\_breadth \times Familiarity$$

We also took additional steps to ensure that unmeasured factors are not causing a potential sample selection bias: Following Heckman (1979) we first computed the Inverse Mills Ratio and then included it as a control variable in all our regression models.

5. **Results**

Table 1 presents the descriptive statistics and correlations for the study variables. There is a significant negative correlation equal to -0.19 between the main explanatory variables, i.e., the R&D firm's breadth and the downstream partner's breadth. To ensure that multicollinearity was not an issue, we calculated the Variance Inflation Factor (VIF) for these variables. In both cases the VIF values were less than 4, indicating no multicollinearity issue.

There are strong positive correlations between the R&D firm's depth and breadth (0.63), and between the downstream partner's depth and breadth (0.52), suggesting that in both partners, the technologically broader firm is also technologically deeper, and vice versa. Again, VIF values were computed for these variables and since they were less than 4, we ruled out the possibility of multicollinearity. The average upfront payment in our sample is 419 million dollars, whereas the average R&D firm's size as to its total assets is 26.8 billion dollars, and that of the downstream partner is 152.6 billion dollars. 15 percent of alliances in our sample are between partners who had already been in previous partnerships with each other.

Insert Table 1 here

Table 2 presents our main findings. In Model 1, we include all the control variables. Results in Model 1 suggest that the size of both partners, as well as their prior familiarity, are associated with higher amounts of upfront payment in the alliance. The downstream partner's size, however, has an effect almost 30 times larger than that of the R&D firm.

Insert Table 2 here

Model 2 tests Hypotheses 1 and 2, namely the direct effects on upfront payment in the alliance by R&D firm's technological breadth (β_7) and downstream partner's technological breadth (β_8). Hypothesis 1 predicts that the R&D firm's breadth of technological knowledge is negatively associated to the upfront payment it receives from the large downstream partner. Consistent with this hypothesis, the coefficient for the R&D firm's technological breadth in Model 2 is negative and statistically significant ($\beta_8 = -0.268$, $p < 0.05$). Hypothesis 2 predicts that the downstream partner's breadth of technological knowledge is positively related to the amount it pays upfront in an alliance with an R&D partner. Consistent with this hypothesis, the coefficient for the downstream partner's technological knowledge breadth in Model 2 is positive and statistically significant ($\beta_9 = 1.502,\ p < 0.01$).

Model 3 tests Hypotheses 3a and 3b, namely the interaction effect of familiarity and the technological breadth of each partner on upfront payment. Hypothesis 3a holds that the familiarity between two partners weakens the negative impact of the R&D partner's breadth on upfront payment. The results in Model 3 support this hypothesis, as the coefficient for the interaction term between familiarity and breadth of the R&D partner is positive and statistically significant ($\beta_{11} = -0.007,\ p < 0.01$). Hypothesis 3b, on the other hand, suggests that the familiarity between two partners strengthens the positive impact of the downstream partner's breadth on upfront payment. However, the results in Model 3 do not show support for this hypothesis as the coefficient for the interaction term between familiarity and breadth of the downstream partner is not statistically significant. These results suggest that familiarity between two partners only helps to reduce the negative impact of the R&D partner's breadth on upfront payment and does not play a moderating role in the relationship between the breadth of the downstream partner and the upfront payment. This suggests that (typically large) downstream partners with broad technological knowledge can oversee the R&D partner's activities in the alliance and mitigate opportunism, with no need of prior familiarity with this firm.

6. **Discussion and conclusion**

This study adds to the literature on R&D alliances and open innovation, particularly, the line of research on the behavioral consequences of R&D alliances as a common form of open innovation practice (for an extensive review of R&D alliance and open innovation see: Frankfort and Hagedoorn, 2023). Following the lead of recent studies (Mindruta, 2013; Mindruta et al., 2016) we take a dyadic approach and examine the knowledge characteristics of both alliance partners i.e., the R&D firm and the downstream firm, and their impact on the downstream firm's willingness to pay large sums of money upfront upon signing the alliance agreement. As per the Frankfort & Haagedorn (2022), in this study we look at the consequences of open innovation for the R&D and the downstream partner and how breadth of knowledge impacts the upfront alliance payment. We found that the breadth of knowledge of the R&D partner and that of the downstream partner have contrasting impacts on the upfront payment in the alliance. The breadth of knowledge of the downstream firms is found to have a positive and greater (compared to that of the R&D firm in terms of effect magnitude) impact on the upfront payment. The breadth of knowledge of the R&D firm, on the other hand, was negatively related to the size of the upfront payment. This is in line with the fear of opportunistic behavior assumed by earlier researchers (Kim, 2011; Lerner and Malmendier, 2010).

These findings corroborate the anecdotal observation that R&D firms (both in our sample and in the industry) are not particularly broad in terms of technological knowledge, rather they are specialized firms working on niche technological topics. It is usually the larger downstream partner which is known for being broad-based in technologies and products. As reported in Table 1, the average downstream partner is more than 5 times broader than the average R&D firm. Considering these statistics, our results reinforce the notion that the breadth of technological knowledge matters more in the downstream partner rather than in the R&D firm in determining the upfront payment in the alliance. The greater breadth of knowledge for the downstream partner makes them more willing to pay for the knowledge that the R&D firms have. There could be two reasons for this result. First, when the downstream partner knowledge base is broad, they have more skills and competencies to monitor the behavior and actions of the R&D firm and therefore believe that they can control the opportunistic behavior on the part of the smaller firm. Second, when the downstream partners have broad knowledge, they are better able to identify and go after opportunities that utilize their knowledge base, can cultivate more absorptive capacity, and can recombine the acquired knowledge to further exploit their broad knowledge base (Arora & Gambardella, 1990; Zhang, 2016).

As per the OI literature, we examined whether "familiarity" helped alleviate the tensions between knowledge sharing and knowledge protection (Bogers, 2010). Consistent with Boger (2010) and Grimaldi et al., (2021) we found that the relational mechanism that built trust and created a layered relationship between the downstream and the R&D partner. Downstream partners were inclined to discount the R&D partners upfront payment less when there were familiar with them. The downstream partner believed that there is more likely to be a collaborative intellectual property strategy and consequently they were willing to provide a higher upfront payment than if they were not familiar with them.

However, the familiarity between partners did not accentuate the positive relationship between the breadth of knowledge of the downstream partner and the amount it paid upfront in the alliance. There are two possible explanations for this: First, the downstream partner may avail of symbiotic opportunities when it has a broad base of technological knowledge and there may be spillover opportunities for collaboration on new technologies that may emanate from working together on the current alliance (Phene & Tallman, 2014). Secondly, when the downstream partner has a broad knowledge base it feels more comfortable about being able to manage the opportunistic behavior that might emanate from the R&D firm because of their proximity and understanding of the product development knowledge, obviating the need for prior familiarity with the R&D partner. Finally, the downstream partner may choose to reward the trust with the R&D partner through means other than the upfront payment.

6.1 Theoretical implications

This study contributes to the ongoing research that examines the interdependencies of partners' technological characteristics and their impact on alliance-level outcomes (e.g., Srivastava & Laplume, 2014; Xu & Cavusgil, 2019; Lyu et al., 2020). While past research has studied the link between technology or product complementarity and the formation or choice of partners in alliances (e.g., He et al., 2020; Johnston & Huggins, 2018; Mindruta et al., 2016), our paper extends that research to demonstrate how the size of an R&D firm's partnership with a larger downstream partner is, at least in part, explained by the interplay between the two partners' technological breadth.

While breadth and depth are the two dimensions of a firm's structuration of knowledge (Esfandyarpour et al., 2024; Farazi et al., 2019; Zhang, 2016), our paper focused on the breadth of knowledge of both parties which happens to be a more observable knowledge dimension as when compared to the depth of knowledge: By merely looking at a firm's patenting or publishing in different fields of knowledge, outside observers (including investors and potential partners) can easily evaluate a firm's breadth of knowledge. This does not mean that depth is not measurable and visible to them. But as this study confirmed, breadth, rather than depth of technological knowledge, plays a more central role in the inter-partner dynamics due to information asymmetry and fear of opportunism. As such, our study contributes to the recent research that considers the role of structuration, rather than the quantity of a firm's knowledge base, in the performance and collaboration outcomes. Scholars have recently shown that the same number of resources can be invested in broadening the firm's knowledge base (entering new knowledge domains) or deepening it (adding to expertise in an existing knowledge domain), or both (e.g., Farazi et al., 2019; Xu, 2015; Zhang, 2016; Zhu et al., 2021). Diverse knowledge base structures are found to have different kinds of effects on firm and alliance performance (Zhang and Baden-Fuller, 2010). Following this line of research, our study sheds light on the dynamics that affect the size of R&D alliances because of both partners having broad knowledge bases.

6.2 Managerial Implications

Alliance size or the total deal size has implications for the overall functioning of the alliance and the individual partners (e.g., Kim, 2011; Robinson and Stuart, 2007). In addition to bringing much-needed funds to the R&D firm, the alliance size can also serve as a signal for improving the market valuation of the firms and is hence of importance both to managers and investors (Janney and Folta, 2003, 2006; Stuart, 2000; Stuart et al., 1999). Our study reminds us of an often-used expression that holds here as well, that is, size matters when it comes to total funds contributed to an alliance. Research suggests that alliance size tends to be key to success in high-tech innovation-driven alliances, particularly those in the biopharma industry given the high-risk, expensive, and time-consuming nature of the product development process (Lerner and Merges, 1998). While contingent payments are in use to manage risks, including those associated with the fear of partners' opportunism, managers of R&D firms might be interested in maximizing the upfront payment that they receive to cover the hefty R&D processes. To do this, they need to be aware of the interplay between the breadth of technological knowledge of the partners and the upfront payment. Our study clearly shows that there is a role for relational dynamics in the open innovation process. When familiar partners form an R&D alliance, there is less fear of opportunism and consequently the R&D partner is compensated as an inner member since the downstream partner believes that there may be a greater selective revealing of intellectual property through collaboration (Bogers, 2011; Grimaldi et al., 2021).

6.3 Limitations and Future Research

Despite the contribution of this study to theory and practice, it has several limitations. First, the sample size is limited due to the data availability from several databases. Second, despite having longitudinal data, the analyses were cross-sectional in nature. Future research can attempt to do time-series analysis with larger samples. Third, this study was specific to the biotechnology and pharmaceutical industries; future research would need to explore the validity of the results with larger multi-industry samples. Lastly, the study largely used secondary data sources to validate the hypotheses, future research can supplement the data with survey data from company managers which could add important qualitative data which would enrich these findings further.

The potential to provide funding to a future competitor influences the downstream partner's evaluation of the R&D firm's knowledge resources (Adegbesan and Higgins, 2010). Future research can therefore delve into the idea that the R&D firm has the potential to ally in the future with a rival of its current downstream partner, and the extent to which the fear of such an event impacts the downstream partner's willingness to pay in the current alliance. The value assessment and value appropriation from an alliance is based on whether the downstream partner firm views the R&D firm as a symbiotic provider of complementary services or as a potential competitor (Carnabuci & Bruggeman, 2009; Carnabuci & Operti, 2013; Vlaisavljevic et al., 2021; Farai et al., 2024). The broader the knowledge base of the R&D firm, the more likely they have access to knowledge in therapeutic areas that, when combined, may directly compete with the downstream partner, providing greater motivation for opportunistic behavior on the side of the R&D firm.

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Figure 1. The conceptual model

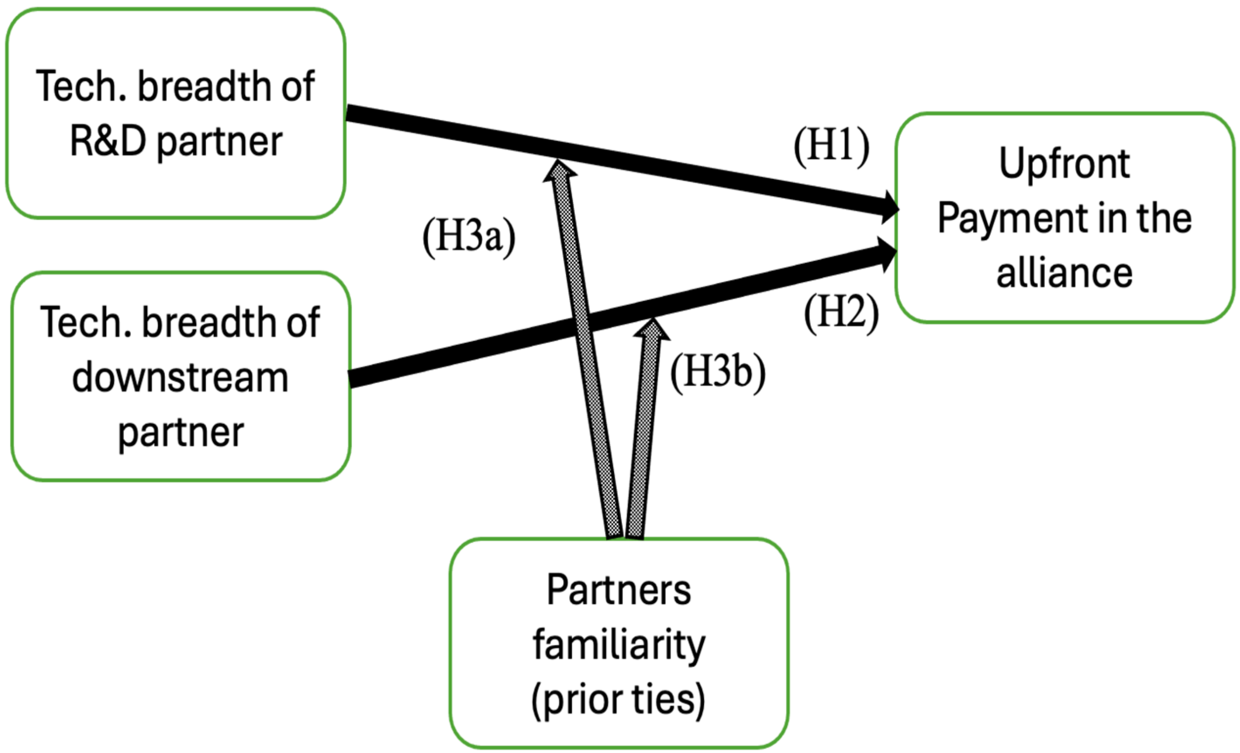

Table 1. Descriptive Statistics and Correlations

	1	2	3	4	5	6	7	8	9	10	11
1. Upfront Payment	1										
2. Equity	0.13	1									
3. Royalty	-0.08	0.01	1								
4. Sales Milestone	-0.06	0.11	0.06	1							
5. Size of R&D firm	-0.06	-0.03*	0.23	0.33	1						
6. Size of DS partner	0.4	0.09*	0.14**	0.07	-0.06	1					
7. Tech Depth of R&D firm	-0.09	0.04	-0.08	-0.43	0.14*	-0.09	1				
8. Tech. Depth of DS partner	0.1	0.12	0.07	0.14	-0.13*	-0.12*	-0.16*	1			
9. Tech. Breadth of the R&D firm	-0.07	-0.04	-0.14	0.11	0.14*	-0.04	0.63**	-0.16*	1		
10. Tech. Breadth of the DS partner	0.16*	0.01	0.05	0.29	-0.16*	-0.05	-0.25***	0.52**	-0.19*	1	
11. Familiarity	0.09*	-0.05	-0.07	0.04	-0.08	-0.06	-0.05	-0.04	0.01	0.02	1
Mean	419.48	0.21	0.11	0.17	26844.3	152579	57.49	537.68	9.44	48.11	0.15
S.D.	733.57	0.44	0.3	0.37	190839	346068	142.45	537.39	16.3	38.14	0.35
Min	0.5	0	0	0	6.5	13.644	1	1	1	1	0
Max	5400	1	1	1	1799337	1653108	1059	2981	144	127	1

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

Table 2:
OLS regressions estimating the associations between partners' breadth of technological knowledge and the upfront payment (N=178 alliances)

Dependent Variable: Upfront Payment (Million USD)	**Model 1**		**Model 2**		**Model 3**	
	Beta	**s.e.**	**Beta**	**s.e.**	**Beta**	**s.e.**
Constant	4.671	0.613	4.215	0.682	4.312	0.67
Year dummies	Yes		Yes		Yes	
Inverse Mills Ratio	0.066	0.07	0.027	0.08	0.02	0.081
Equity (yes=1)	0.044	0.067				
Royalty (yes=1)	0.03*	0.012				
Sales Milestone (yes=1)	-0.058	0.067				
Size of R&D firm	0.101*	0.073	0.173**	0.084	0.202**	0.081
Size of DS partner	3.013***	0.851	2.751***	0.863	2.51***	0.852
Depth of R&D firm's knowledge	-0.708*	0.154	-0.619*	0.144	-0.521†	0.193
Depth of DS partner's knowledge	0.031	0.053	0.033	0.054	0.001	0.501
Breadth of R&D firm's knowledge			-0.268*	0.109	-0.32**	0.112
Breadth of DS partner's knowledge			1.502**	0.4333	0.518**	0.151
Partners familiarity			0.081**	0.026	0.0411**	0.012
Familiarity x Breadth of R&D firm					0.007*	
Familiarity x Breadth of DS partner					0.014	0.065

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