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Technological Knowledge Base, R&D Organization Structure and Alliance Formation: Evidence from the Biopharmaceutical Industry

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Abstract

We explore how an incumbent firm's internal knowledge and organization structure influences its strategic alliance formation. We propose that the firm's knowledge breadth and the centrality of its R&D organization structure positively influence its absorptive capacity, and consequently, its propensity to form strategic alliances. We also argue that the centrality of the R&D organization structure may be a substitute for the breadth of the knowledge base. We validate our ideas using data on 2 647 strategic alliances formed over the period of 1993 to 2002 by 43 major biopharmaceutical firms in the U.S. and Europe. Discussion focuses on the application of the knowledge-based view of the firm to strategic alliance research. The implications for public policy in the biopharmaceutical industry are also emphasized.

Keywords: Strategic alliance; Knowledge breadth; Organization centrality; Strategy to ally

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1. Introduction

In technology-based industries, incumbent firms frequently form strategic alliances – collaborative agreements involving exchange, sharing, or co-development of products, technologies or services – with smaller firms and new entrants (Gulati, 1998; Hagedoorn, 1993). The main motivation for the allying firms is either to *learn*, i.e., transfer and absorb the knowledge of the partners in order to explore new knowledge (Dyer and Nobeoka, 2000; Kale et al., 2000; Khanna et al., 1998; Hamel et al., 1989), or to *access* the partner's knowledge assets in order to exploit complementarities (Grant and Baden-Fuller, 2004). Because "absorptive capacity" (the capacity of firms to learn and absorb the new knowledge) is seen as central to the effectiveness of technology-based alliances (Cohen and Levinthal, 1990), debates about the determinants of alliance formation typically revolve around the question of what are the dimensions of absorptive capacity and how it is measured.

It is commonly thought that absorptive capacity is the result of cumulative path-dependent R&D efforts by the firm (Baum et al., 2000; Hennart, 1988; Powell et al., 1996). And until now, many measure the firm's absorptive capacity by calculating the size of past R&D spending and relate this to the firm's proclivity to form alliances (e.g., Arora and Gambardella, 1994; Harrigan, 1985; Kleinknecht and Reijnen, 1992; Mol, 2005). However, these studies did not find conclusive results on the relationship between firm alliance behavior and these measures of absorptive capacity.

We argue that there are two major theoretical causes to the mixed findings. First, these studies failed to capture the extent to which firms vary substantially in their ability to transform R&D inputs into absorptive capacity. In particular, the same amount of input may be used to broaden the knowledge base, or merely to deepen existing knowledge disciplines (Wang and von

Tunzelmann, 2000). Knowledge breadth is more closely linked to absorptive capacity, because it affects a firm's capability to link internal existing knowledge to the external new knowledge, and eventually its propensity to enter alliances. Second, the prior studies omitted the important influence of management generally and R&D organization structure in particular on the connection between R&D inputs and absorptive capacity. Particularly, a centralized R&D structure may facilitate dense internal communication flows and increase firm absorptive capacity (Jansen et al., 2005; Taggart, 1993), and this in turn may influence the willingness of firms to enter into strategic alliances.

In this research we rectify these deficiencies and thereby aim to offer a new understanding of firm alliance formation from the perspectives of firm internal knowledge base and organization structure. We explore the influence of the two constructs – the breadth of knowledge base and the centrality of R&D organization structure – on the propensity of large incumbent firms to form alliances with small firms. Our research site is the biopharmaceutical industry, which is characterized by radical innovation, adaptation pressures, and frequent alliances between large pharmaceutical firms with new biotechnology firms (NBFs) (Powell et al., 1996). We test our ideas using a panel database of 2 647 strategic alliances formed over the period of 1993 to 2002 by 43 major biopharmaceutical firms in the U.S. and Europe. Not only do we find that each of the constructs is important as predicted, but we also find that there is a strong substitution effect between knowledge breadth and organization structure.

Theoretically, this study helps deepen our understanding of both absorptive capacity constructs and the modeling of a firm's alliance behavior. First of all, it reminds us that R&D expenditures are not a direct determinant of "absorptive capacity"; management has a role to play through its choice of how to direct R&D expenditures and how to organize the firm. Taking

these ideas forward it is therefore possible to show theoretically and empirically that the propensity of firms to form alliances is strongly influenced by the structure as well as the quantity of its knowledge base.

This study has important practice implications too. First, the finding that the organization of internal R&D (centrality) influences a big pharmaceutical firm's propensity to ally is valuable for policy makers in those countries that wish to develop new research parks and incubators (Roijakkers et al., 2005). Second, the finding that a firm's R&D centralization is substitute for its knowledge breadth in influencing alliance behavior suggests that management can decrease or increase the firm's absorptive capacity even after expenditures have been made. This finding suggests that major pharmaceutical firms may be unwise to split research capacities among divisions as this weakens the path-dependent feature of technological knowledge development (Nelson and Winter, 1982).

2. Theoretical background and hypotheses

Research on strategic alliances has blossomed since the 1980s (Glasmeier, 1991; Hagedoorn, 1993), with one major strand attempting to understand the motivations and abilities of a firm to ally (c.f. Gulati, 1998; Ireland et al., 2002). In many high-tech industries, the incumbents do not face the problem of insufficient alliance *opportunities* offered in the market (Roijakkers et al., 2005); rather their propensity to form alliances with new entrants is largely determined by their *abilities* to benefit from alliances (Ahuja, 2000; Eisenhardt and Schoohoven, 1996). As noted in the introduction, this ability to benefit from external knowledge when undertaking fundamental technological work has been linked to the concept of "absorptive capacity" (Cohen and Levinthal, 1990), which states that prior related knowledge confers an

ability to recognize the value of new information and to assimilate and apply it to commercial uses. The general view is that the development of absorptive capacity is cumulative and path-dependent (Nelson and Winter, 1982) and involves intensive internal R&D investment (Ahuja, 2000; Hagedoorn, 1993). Hence, as said earlier, most past work on the propensity to form technological-alliances has taken a rather crude approach to measuring absorptive capacity, and reported mixed evidence. While some found that the firms investing actively in internal technological knowledge development are more likely to enter alliances (Arora and Gambardella, 1994; Dyer and Singh, 1998; Kinder, 2003; Quinn, 2000), some found a negative relationship (Harrigan, 1985; Pisano, 1990), and the others did not find constant relationship at all (Kleinknecht and Reijnen, 1992; Mol, 2005).

It is worth unpicking in more detail the two major theoretical reasons for the inconclusive findings. First, and perhaps the most important reason, is that the same *quantity* of R&D *input* may affect different firms differentially, in that R&D input can be used to either deepen or broaden the existing knowledge base. Take the example of an established pharmaceutical firm, which is used to hiring chemists for its R&D lab. If it starts to recruit biotechnologists and purchase relevant equipment (e.g. gene splicers), its technological knowledge base becomes broader and its absorptive capacity is consequently increased. However, if it merely recruits more chemists who undertake similar tasks to what the firm did before, its knowledge base will become deeper. The firm may improve its ability to do the particular work; but its absorptive capacity will not be substantially changed, at least in the short run (Cohen and Levinthal, 1990).

The second reason for these inconclusive findings is the failure to include the R&D organization structure, an important aspect of knowledge management, in their models of alliance formation (Argyres, 1996; Argyres and Silverman, 2004). Long time ago Henderson and

Clark (1990) argued that centralizing research may increase the firm's architectural knowledge about how components of the systems interact, but few have explored this issue in the context of absorptive capacity. One study that fills the gap is Jansen et al (2005), who showed that improved co-ordination within a unit increased absorptive capacity. Although some studies have addressed the impact of organization structures on innovative performance (Chacar and Lieberman, 2003; Dunning, 1994; Pearce and Singh, 1992; Taggart, 1993), no studies have examined the influence of R&D organization on alliance behavior.

The research purpose of this study is to offer an improved modeling of firm alliance behavior primarily based on an improved understanding of how to measure absorptive capacity. Considering the theoretical problems in the prior studies, in this study we will measure absorptive capacity directly from knowledge base (output). Moreover, we will examine how the way the firm organizes its R&D can influence its absorptive capacity and consequently alliance formation. Finally, we are going to explore more complex model of firm alliance behavior by checking the interaction effects of knowledge base and R&D organization structure.

2.1. Breadth of knowledge base and alliance formation

Drawing on Wang and von Tunzelmann (2000) we define the breadth of knowledge base as the range of knowledge areas that a firm possesses. A firm with a broad knowledge base is therefore familiar with many territories on the knowledge landscape, and thus is capable of trying more paths in order to explore new regions (Kauffman et al., 2000). If we take the biotech industry since the 1970s, the drug development process requires a successful biopharmaceutical firm to master a very wide range of technological disciplines, including molecular biology, physiology, biochemistry, analytic and medicinal chemistry, crystallography, pharmacology and

so on. As Peteraf (1993) points out, the employment of a Nobel prize-winning chemist is unlikely, in itself, to be a significant source of competitive advantage, and incumbents still need to learn or access a large range of complementary knowledge from new and smaller firms to maintain a high performance in drug development and commercialization (Arora and Gambardella, 1990; Rothaermel, 2001).

We predict that a broad knowledge base in a technology-based industry assists an incumbent in learning from alliances. In general, knowledge diversity increases absorptive capacity, which facilitates the innovation process by enabling the firm to make novel associations and linkage (Cohen and Levinthal, 1990). A diverse knowledge base in related territories may ease the process of absorbing the partners' knowledge, especially tacit knowledge, by associative learning (categorizing new knowledge into which prior knowledge is organized), and then by establishing linkages with pre-existing concepts (Bower and Hilgard, 1981; Lindsay and Norman, 1977; Polanyi, 1958). A diverse knowledge base also allows the firm to build up "architectural competence" by integrating dispersed knowledge from the partners together into a coherent whole (Henderson and Cockburn, 1994).

A broad knowledge base also provides a firm with a stronger ability to recognize and mobilize the real option values embedded in new knowledge purchased from the partners (McGrath, 1999). First, an incumbent with a diverse knowledge base is more able to recognize the potential value that may unfold as technology develops, and so identify which new technological projects offered by prospective partners offer best value (Arora and Gambardella, 1990). Second, based on a better understanding of the new technology, it can also craft better contracts to regulate alliance activities and make more secure future benefits (Baden-Fuller et al., 2006; Reuer and Tong, 2005). The prevalence of options thinking is noticeable in drug

development and commercialization contracts. Pharmaceutical firms usually specify their instalment investment as contingent on the performance of partners in meeting milestone targets (Reuer and Tong, 2005).

The strategic alliance literature has provided empirical evidence of the value of a broad knowledge base in alliance formation. Henderson (1994) with cardiovascular drug discovery sector data, Orsenigo et al. (2001) with biotech industry data, Brusoni et al. (2001) with aircraft engine control systems data and Mowery et al. (1996) with cross-sectional data have found that established multi-technology R&D-intense firms are very capable of absorbing new knowledge generated outside firm boundaries. This is in spite of major technological discontinuities and breakthroughs initially resulting in the growth of specialized technology producers. Drawing upon the argument and empirical evidence, we predict a positive impact of a broad knowledge base on the formation of strategic alliances.

H1. The broader the firm's technological knowledge, the more likely the firm will form new strategic alliances.

2.2. Centrality of R&D organization structure and alliance formation

The centrality of R&D organization structure helps determine the extent to which the technological knowledge base is concentrated at the corporate level or dispersed at the divisional level (Argyres, 1996; Argyres and Silverman, 2004; Chacar and Lieberman, 2003). When the knowledge is centrally located, there is strong central planning and control by the corporate-level executives, while a decentralized knowledge base is developed extensively within divisions or business units.

A centralized R&D organization structure may increase the possibilities that the incumbent will benefit from alliances. The major reason for this is that centralization helps to facilitate dense internal communication flows and increase firm absorptive capacity (Jansen et al., 2005; Taggart, 1993). According to Henderson and Cockburn (1994), the managers or researchers in divisions are repositories of "component knowledge" (in the biopharmaceutical industry, the knowledge about a few particular technological disciplines or disease areas); but the "architectural knowledge" (the knowledge of how to incorporate the multi-disciplines in order to deal with one particular disease) tends to reside in informal communication channels between the divisions, and such communication forms "information filters" shared by the divisions. The channels (and associated filters) become deeper as existing drugs develop, screening out new drug or technology alternatives beyond the previous domains of inter-division communication. Such a screening-out problem is more serious when the new knowledge comes from the other organizations. Because understanding, evaluating and exploring the new knowledge require more new interactions between components, informal communication becomes more difficult between the divisions and across organizational borders. Hence learning or accessing knowledge through alliances is likely to be screened out in divisions.

In comparison, centralized knowledge holders may be better able to appreciate and explore innovation and facilitate knowledge exchange with alliance partners. This is because communication inside the corporate lab is better controlled by the top management, and the researchers in centralized R&D labs are less deeply engaged in local communication channels, and in turn, are less subject to the associated information filters (Argote and Ingram, 2000; De Meyer, 1993). Thus the incumbent is better able to evaluate, assimilate and apply the new knowledge provided by partners.

There are several other reasons that explain why incumbents with a centralized R&D organization structure form more alliances. Centralized R&D management helps prevent potential leakages of important knowledge to competitors during the alliance process (Dunning, 1994). Moreover, a firm with a centralized R&D structure may achieve economies of scale and scope in R&D operations through a portfolio of alliances (Pearce and Singh, 1992). Such a firm is more likely to be adept in evaluating new technologies, designing alliance contracts, and raising the value of the project (Baden-Fuller et al., 2006; McGrath, 1999; Reuer and Tong, 2005). Hence, the incumbents with centralized R&D benefit more from alliances, and thus are more likely to form alliances.

H2. The more centralized the firm's R&D organization structure, the more likely the firm will form new strategic alliances.

2.3. Interaction effects of knowledge breadth and centrality

The argument above suggested the importance of two constructs of an incumbent knowledge – its breadth and its R&D organization structure – on the decision to form strategic alliances. The same group of researchers when managed under different organizational structures will generate different patterns of communication within the group and between the group and external knowledge providers. Hence, their ability to evaluate, assimilate and apply new knowledge from alliance partners will vary. So, how do the two constructs interact when they are investigated together?

One strand of strategic alliance literature suggests that when a firm has relatively sufficient knowledge for in-house R&D development, it has less incentive to approach alliance

partners (Ahuja, 2000; Eisenhardt and Schoonhoven, 1996). The basis of this theory is the trade-off between the benefits and pitfalls of knowledge exchange through alliances. Although a firm can learn or access new knowledge from its partners, it also has to share its knowledge with the partners, which may harm its competitive advantage (Mitchell and Singh, 1992). Further, such well-endowed firms may stand to benefit much less from their partners than their partners can benefit from them (Hamel et al., 1989; Kale et al., 2000; Khanna, et al., 1998). Therefore, it is likely that a firm possessing rich knowledge for in-house development may have a low inducement to enter into alliances. In this study, since the two constructs – broad knowledge base and centralized R&D structure – are associated with stronger absorptive capacity, which improves in-house development capabilities, the firm that happens to possess both features will be less likely to enter alliances. In other words, the impacts of both constructs on alliance formation may be substituted for each other. Hence, we predict that:

H3. When the firm's R&D organization structure is more centralized, the positive relationship between knowledge breadth and the likelihood of new alliance formation becomes weaker.

3. Methods

3.1. Research setting

The research context is that of large pharmaceutical firms active in the biotech sector in the U.S. and Europe. Two considerations motivated the choice of the biopharmaceutical industry as the setting of the study. First, this industry has been identified as being under radical innovation (Hagedoorn, 1993), making it an ideal context to analyze the technological innovation behavior of incumbent pharmaceutical firms (Katila and Ahuja, 2002). Second, in this industry,

innovation knowledge is dispersed among big pharmaceutical firms, new biotechnology firms (NBFs) and academic organizations, and consequently it is characterized by very high alliance activities (Powell et al., 1996). Although many studies have observed the impact of alliance on innovation performance in this industry (e.g., Rothaermel, 2001; Rotheaermel and Deeds, 2004), few have examined how the alliances are formed.

3.2. Sample

Our data set analyzes the alliance activity of 43 firms over the period 1993 to 2002. The 43 sample firms are chosen because they are the most active companies in U.S. biotechnology patent application as retrieved from the Derwent Biotechnology Abstract (DBA) database. DBA covers all biotechnology patent applications since 1981 and provides 12 technology classes and 30 sub-classes in biotechnology, as seen in Appendix I. Each patent may cover one or more technological areas. As biotechnology appears to be a vital competence for innovation in drug development, patents play a central role in the firm's strategies. Since a patent by definition includes a description of a technical problem and a solution to that problem (Walker, 1995), patent data provide a consistent chronology of firms' knowledge accumulation (Shan et al., 1994). The 43 sample firms can therefore be considered knowledge leaders in the biopharmaceutical industry.

The 43 sample firms are good representatives of established pharmaceuticals with large R&D investment. Their average annual sales during the period 1993-2002 were about US$7.9 billion, operating profit (EBIT) about US$1.0 billion, 27 173 employees, and R&D intensity (R&D expenditure per employee) about US$ 1 210.

3.3. Dependent variable: new alliances

The dependent variable is the number of new strategic alliances formed by a firm in one particular year. We employed *BioCentury*, an online industry database that reports and classifies press releases by biotechnology firms, to retrieve firm alliance data from 1993 to 2002. *BioCentury* has comprehensive coverage of U.S. and foreign companies actively involved in biotech R&D. This database is highly reputed and considered to be reliable among industrial practitioners, although it is not much used by academic researchers because of its high fees. Considering the nature of the large firms, we included the alliances of all the divisions and subsidiaries of a sample firm with reference to *Who Owns Whom* (U.S., U.K. and Ireland, and Continental Europe editions) and the *Directory of Corporate Affiliations*. The alliances of divisions and subsidiaries were counted in as if they were made by the parent firms. The sample firms were not very active in mergers/acquisitions during 1993-2002, except for one merger between Glaxo (sample firm) and SmithKline Beecham, two acquisitions by Johnson and Johnson, and one acquisition by Novartis, in which cases the alliances and patents of the merged/acquired firms are counted in under the name of the sample companies. The reason for choosing 1993 as the starting year is because the biotech industry has mushroomed since 1993, with U.S. revenues increasing from $8 billion in 1992 to $39.2 billion in 2003 (BIO, 2004).

We identified 2 876 alliances and for each one identified the partner. In total 988 partners were involved in these alliances. Among them, only two organizations joined in more than 20 alliances (27 and 24 respectively), 23 organizations joined in 10-20 alliances, 392 organizations joined in 2-9 alliances, and 571 organizations appeared only once. We cleaned the database by deleting the alliances in which the partners were one of the focal firms or academic organizations. The purpose of this was to keep only NBFs as alliance partners, so that the motivations for our

focal firms to enter alliances were comparable. In total we excluded 21 alliances in which 14 academic organizations were involved and 208 alliances in which 22 focal firms were involved. After these exclusions, 2 647 alliances remained.

3.4. Independent variable: breadth of knowledge base

It is well known that it is difficult to measure organizational knowledge, and thus technological knowledge profile, accurately (King and Zeithaml, 2003). Patents represent a well-recognized solution to the problem, but in turn suffer from problems. One major concern is that the propensity for patenting varies considerably across industries (Cockburn and Griliches, 1987), a problem we avoided by considering only one industry and being sensitive to the nature of patents (Pavitt, 1988). For our purpose, patents are useful because we can classify the knowledge embodied in a patent to knowledge classes and so use them to measure the breadth of a firm's knowledge base.[1]

We measured the *breadth of knowledge base* by counting the number of technological sub-classes in DBA classification (see Appendix I) in which the firm has been granted patents in the 5-year window (Birkinshaw et al., 2002; Granstrand and Sjolander, 1990). We took a 5-year window of prior patents for each firm and each year to assess the breadth of a firm's stock of knowledge. For example, any of the knowledge measures for year 2000 for any firm is the sum of the patents granted to the firm in 2000, 1999, 1998, 1997 and 1996 (Henderson and Cockburn, 1994). The 5-year window for patenting attenuates annual fluctuations and thus may capture a firm's patenting propensity more accurately. In addition, it is reasonable to believe that a firm's decision to enter alliances is based on the stock of its knowledge base. Using a 5-year time

[1] We did not use patent citation in calculating knowledge breadth, because our main interest is not the novelty of patents, which was well captured by the citation. Moreover, "the recency of the emergence of biotechnology in combination with the patent citation time lag made this approach infeasible" (Rothaermel and Deeds, 2004, pp. 210).

window is also consistent with prior research (e.g., Ahuja, 2000; Rothaermel and Deeds, 2004). For all variables we composed data for 1992 through 2001, one year lag before the dependent variable. We also considered the nature of the large and multinational firms. The patents of divisions and subsidiaries were counted in under the name of their parent firms.

3.5. Independent variable: centrality of R&D organization structure

We followed the work of Argyres and his colleagues in measuring *centrality of R&D organization structure* (Argyres, 1996; Argyres and Silverman, 2004). The data were collected from various sources. The *Directory of American Research and Technology* (1991-1998) was the primary source of information on U.S. firms. This contains information on the number of researchers in R&D laboratories in each division/subsidiary for some of our sample firms. The lack of researcher-counts for all firms precludes our creating a continuous measure of R&D centrality. For the eight firms that did not release such information, we estimated the size of each lab based on the number of fields of R&D listed for the lab, which is highly correlated with the number of researchers. We categorized a firm's R&D structure as "centralized", if no lab was under any business divisions; and "decentralized", if the firm had no central lab under corporate headquarter. Following Argyres and Silverman (2004), we refined "hybrid" structure into three categories. Hybrids with a ratio of central to divisional researchers greater than 1.3 were categorized as "centralized hybrids"; those whose ratio was below 0.7 were categorized as "decentralized hybrids"; those in the middle were "balanced hybrids". In nature, the "centralized hybrids" typically possess a relatively large corporate lab located at corporate headquarters, and relatively small divisional labs elsewhere. The "decentralized hybrids", in contrast, have large divisional labs – often located within separately incorporated divisions – and a relatively small

central lab. Essentially, the R&D structure of all firms remained stable over the years 1991-1998, which is the coverage of the directory. We checked company annual reports and 10K statements and company histories when available, and we found a similar result for the years 1999-2001[2]. This reinforced the study of Henderson and Cockburn (1994), which reported the stability of a firm's R&D structure in the pharmaceutical industry. Hence, the *centrality of R&D organization structure* was constant over the research years 1992-2001 for each firm. To check the validity of the data, we compared ours with those of Argyres and Silverman (2004), and found that the proportion of each category is similar between the two samples, thus verifying our measurement. To collect information on the European firms, we used the *Directory of European Research and Development* in various years. The data were verified using company annual reports and 10K statements, company histories when available, and newspapers and magazine articles.

We then created five categorical variables that capture each of the R&D structure types, where "decentralized" structure was the reference group. In addition, we also created a *centrality scale* which increases with overall R&D centralization, from 1= "decentralized" to 5= "centralized". Although this scale has an unsatisfactory assumption – the distance between each adjacent category is the same – it has the advantage of ease of interpretation in some of the models shown later.

3.6. Control variables

We introduced a number of control variables, which might influence firm alliance behavior according to previous research. The first was the *concentration of knowledge base*. A

[2] We found that of the 43 companies, only Abbott changed their R&D structures during 1999-2001. Abbott formed the Global Pharmaceutical Research and Development (GPRD) organization, unifying all research and development at Abbott into a single unit in 2000, at which point its technological alliances increased from average 3 per year to 11 in year 2001 (http://www.abbott.com/GPRD/GPRD_AboutUs.htm). We then treated "centrality" for Abbott in year 2000 and 2001 as missing data in the regressions.

firm that has a profile of 10%-10%-80% patent granted in 3 DBA sub-classes, for instance, would have a different knowledge base from a firm with the same knowledge breadth but which has a profile of 33%-33%-33%. *Concentration* is computed in two steps (Soete, 1987). In the first step, the *Revealed Technological Advantage (RTA)* is computed as follows:

$$RTA_{it} = \left(\frac{P_{it}}{\sum_{t} P_{it}} \right) \Bigg/ \left(\frac{\sum_{i} P_{it}}{\sum_{it} P_{it}} \right) \qquad (1)$$

where *P* is the number of patents held by firm *i* in technology class *t*. Eq.(1) is the ratio of the share of firm *i* patents falling in technology class *t*, over the share of all patents falling in that technology class. In the second step, we compute the coefficient of variation of all the firm's *RTA* measures:

$$Concentration = \frac{\sigma_{RTA}}{\mu_{RTA}} \qquad (2)$$

Eq.(2) says that the concentration of the firm's knowledge base is high when the firm has developed a high relative technological advantage in one or a few technology classes.

Second, we controlled for the stages of alliances. Following Rothaermel (2001) and Rothaermel and Deeds (2004), we classified each alliance as either early stage (i.e., exploration alliance) or later stage (i.e., exploitation alliance) according to the initiative stage of the alliance contract. The alliances relevant to basic research and drug discovery (preclinical trials) were coded as early stage alliances, and those targeting commercialization (drug development in clinical trials, manufacturing, FDA approval and marketing/sales) were coded as later stage alliances. To check our coding, we used second researchers to examine about 50 percent of the data points. We found that inter-rater reliability was 0.91, well above the conventional cut-off

point of 0.70 (Cohen and Cohen, 1983). The 2 647 alliances included 1 063 early stage alliances and 1 584 later stage alliances.

Third, we controlled for *R&D intensity*, measured by the ratio of R&D expenditure to the number of employees. Fourth, we controlled for *firm size* using the log value of the number of employees. Fifth, we controlled for *operating profit (EBIT)*, since slack financial resources may provide a firm with a strong ability to form alliances (Eisenhardt and Schoonhoven, 1996). Sixth, we controlled for national effects by adding one dummy *Europe*, while keeping U.S. companies as the reference group. Finally, we controlled for firm heterogeneity (e.g., alliance strategy) by including a one-period-lagged dependent variable Y_{t-1} (Heckman and Borjas, 1980)[3].

4. Findings

Table 1 shows the descriptive statistics and correlations for all variables. It indicates that on average a firm formed 4.3 alliances (1.6 in early stage and 2.7 in later stage) each year. The absence of high correlations between knowledge breadth and R&D centrality, and between these and the controls suggests that multicollinearity is unlikely to be problematic in this analysis. Moreover, prior to the creation of interaction items, knowledge breadth and R&D centrality scale were mean-centered to reduce the potential multicollinearity (Aiken and West, 1991).

Insert Table 1 about here

We applied negative-binomial models to test the hypotheses. Like Poisson regression, the negative-binominal model treats the dependent variable as a count variable but allows for a direct measure of heterogeneity (Cameron and Trivedi, 1986). Estimating heterogeneity not only

[3] We also controlled for the experience of firms in forming and managing alliances using the cumulative number of alliances in the past three years (Simonin, 1997). But as this variable is highly correlated with Y_{t-1} (r=0.819), we integrated only Y_{t-1} in the regression in order to keep a large sample of alliances.

relaxes the stringent Poisson assumption of equal mean and variance in the error term but also accounts for omitted variable bias (Walker et al., 1997). We also applied Poisson regressions, and found no substantial differences.

Table 2 depicts our statistical analysis results. Model 1 is the base model that includes only control variables. We introduced variables in differing combinations to test for robustness, and we found stability in our results. For the sake of brevity we only show two models (2 and 3) that include both direct and interactive effects of knowledge breadth and centrality of R&D organization. In model 2 we measure centrality using the *centrality scale,* and in model 3 we replace the *centrality scale* with a vector of categorical measures with *decentralization* as the reference group, which allows us to test for non-linearity.

Insert Table 2 about here

Hypothesis 1 predicts a positive relationship between knowledge breadth and alliance formation. In models 2 and 3, the coefficients on *breadth* are positive and significant (B=0.145, $p<0.01$; B=0.178, $p<0.01$ respectively). So H1 is supported.

Hypothesis 2 predicts a positive relationship between R&D centrality and alliance formation. It is supported by the result in model 2 with the measure of *centrality scale,* which has assumed that decentralization-centralization effects are linear, since its coefficient is positive and significant (B=0.207, $p<0.01$). Model 3 with categorical variables of centrality further explores this effect. By and large, the linearity assumption stands, since except for *decentralized-hybrid* the effects of the other dummy variables of organizational structure on alliance formation are significantly higher than the omitted *decentralized* category.

Hypothesis 3 states negative interaction effects of breadth and R&D centrality. Model 2 supports it with the measure of *centrality scale*, since the product term *breadth*centrality scale* is negative and significant (B=-0.069, $p<0.01$). Model 3 also supports H3 with the categorical variables of centrality, except that the effect of *decentralized-hybrid* is insignificant relative to the omitted *decentralized* category. Figure 1 graphically plots the interactions. We used one standard deviation between and above the mean as the range for *centrality scale*, and the other variables were constrained to their mean values (Aiken and West, 1991). The two lines in Figure 1 indicate that overall the *breadth* of knowledge base has positive impact on resource acquisition; and its impact is strengthened when *centrality scale* is low rather than high.

Insert Figure 1 about here

The results of the control variables have some interesting insights. *Knowledge concentration* showed somewhat negative effects. It suggests that a firm with evenly dispersed R&D capabilities has a slightly higher likelihood of using alliances. The dummy variable *later-stage alliances* did not show significant results. It implies that after checking for the influences of the other factors, the firms have a similar propensity to enter early and later stage alliances. Similarly, *R&D intensity* did not show significant influence on alliance formation, which suggests that its impact was perhaps mediated by the other knowledge and organizational variables included in our model. *Firm size* and *EBIT (profit)* showed significantly positive effects, which suggests that the firm with munificent (slack) resources is more able to explore new technological development, as well as exploit market opportunities with alliance partners. It also implies that entering alliances is a way of improving the efficiency of firm knowledge-utilization given the economics of scale and scope in knowledge (Grant and Baden-Fuller, 2004). The

coefficient of *Europe* did not appear to be significant, suggesting that the European context did not skew results. Finally, the consistent and positive effects of Y_{t-1} suggest the path-dependence feature of a firm's alliance activities (Nelson and Winter, 1982).

We conducted extra tests to further explore firm alliance behavior at the different stages of alliances. The literature seems to suggest that compared with later stage alliances the early stage alliance activity would rely more on a broad R&D knowledge base as those partnerships are exploratory, fundamental and generic in nature (Argyres and Silverman, 2004). We tested this hypothesis by including the product term *later-stage alliances*breadth* in the model. But no significant results were found. We also split the samples into two groups with early-stage alliances as one group and the rest in the other group, and tested H1 to H3. All hypotheses were supported by both sub-samples. The result implies that the impacts of knowledge breadth and organizational structure on firm alliance decision are consistent over the different stages of alliances.

We undertook some further robustness tests. We first added *centrality scale*^{2} to check the non-linearity of the effect of *centrality scale*, but did not find significant results. Then, we changed the measures of the control variables. For instance, we changed the measure of *firm size* by the value of fixed assets, the measure of *R&D intensity* by calculating log (R&D investment) or the ratio of R&D investment over the value of fixed assets. The results remained the same for the variables of interests. In addition, we modified the models by excluding Y_{t-1}, since this variable might absorb too much effect stemming from firm features and thus lead to the non-significant results of the other variables. We did not find significant change either. In sum, our results are robust to a satisfactory level.

In sum, all of our hypotheses are supported. The broader the technological knowledge base of the firm, the more likely it is to form technological alliances. Likewise, a more centralized R&D organization structure has the same effect. And, significantly, there is a substitution effect between these two constructs. Finally, the importance of knowledge breadth and organization structure on firm alliance decision is stable as between early and later stage of alliances.

5. Discussion

Because absorptive capacity is seen as central to a firm's motivation to benefit from alliances, a central theme of this paper was to deepen our understanding of how to understand and measure this important concept. Absorptive capacity as a concept is a measure of a firm's ability to accumulate and mobilize knowledge (Cohen and Levinthal, 1990). Hitherto, many researchers appear to have assumed that expenditures on R&D automatically translate into absorptive capacity. But our research confirms what several researchers have argued: the process of creating and mobilizing knowledge is quite complex. Unlike Jansen et al. (2005) we did not explore the micro-process by which individual managers influence the conversion process. However, we did investigate how managerial choices such as the organization of the firm interact with knowledge stocks to alter absorptive capacity. This approach, as noted earlier, is consistent with taking an architectural view of knowledge (Henderson and Clark, 1990). It is also consistent with the view that a firm's ability to mobilize its knowledge is more than just identifying what individual units know (Grant, 1996). We know that mobilizing embedded knowledge is a form of dynamic capability and firms differ greatly in this respect (Teece et al., 1997). Our research brings greater clarity to one dimension of this concept of dynamic

capability, by suggesting that centralization of research activities may enhance firms' capacity to renew and change. This view is congruent with themes in the literature on strategic renewal that argue for centralization to generate new ideas in the renewal process (Stopford and Baden-Fuller, 1994).

Our work has a more general message for the knowledge-based view of the firm, which sees the role of the firm as the integrator of knowledge (Kogut and Zender, 1992; Spender, 1996). There is a strong view in the resource-based view of the firm that what happens inside the firm is critical to its development path (Barney, 1991). Yet the knowledge-based view takes a broader perspective. We know that inter-firm collaboration is profoundly important in a firm's development in certain industries, especially those involving high-technology. For example, the frequency of alliances in biopharmaceutical industry in this study was on average greater than 4 a year and they were wide in their scope. This reinforces the suggestion of many prior studies that the firm should be seen as an institution that integrates knowledge both within and across the boundaries (e.g., Grant and Baden-Fuller, 1995, 2004).

Obviously our work has an important bearing on our understanding of how to model alliance behavior, something called for by Dyer et al. (2001). The paper shows that the incumbent's alliance motivations are strongly influenced by the breadth of the knowledge base and the way the internal R&D knowledge is organized (centrality). We also found that the centrality of the R&D organization can substitute for the power of the knowledge base.

As underlined by Arora and Gambardella (1994), the benefits of R&D centralization – rapidity of decision making, strong capacity to renew knowledge and achievement of the economies of scale or scope of knowledge – reinforce the advantage of large incumbents in potentially benefiting from alliances, since the large incumbents already possess complementary

assets as well as strong knowledge integration capabilities (Kogut and Zender, 1992; Teece, 1986). Our finding appears to support this point. It also casts doubt on the claims that R&D centralization is unwise because it reduces the flow of external know-how into the firm (Chacar and Lieberman, 2003), creating bureaucratic diseconomies (Williamson, 1991), higher monitoring cost (Ouchi, 1978), and less internal competition (Porter, 1990). However, it merits noting that in this paper we did not examine the performance of the alliances directly (e.g., new drugs are developed successfully). Our study only shows that R&D centralization may provide the conditions for the incumbents to benefit from alliances, which could improve subsequent alliance performance if incorporated with their strong alliance management skills. We will discuss this further in the "limitations and future research" section below.

The findings of the substitution effect between knowledge breadth and R&D structure centrality and the negative effect of knowledge concentration on alliance formation make sense of Rothaermel and Deeds (2004)'s assertion in their research on the biotech industry that under some circumstances "internal resources are substitute for external alliances" (p. 206). This study suggests two such circumstances: (1) the firm possesses both broad and centralized knowledge bases, and (2) it has concentrated technological strength in a few areas. Both mean the firm has the strong capability to conduct in-house development. This reinforces the view that there is a trade-off between the benefits and pitfalls of knowledge exchange through alliances (Ahuja, 2000; Eisenhardt and Schoonhoven, 1996).

6. Policy and managerial implications

This study has important implications for public policies towards the biopharmaceutical industry. Most importantly, this study questions public policies which stimulate strategic

alliances at the stages of early drug discovery between big pharmaceutical firms, NBFs and academic organizations. Our study shows that large incumbents not only ally to explore new knowledge with NBFs but also to access complementary assets as illustrated by the number of later stage alliances compared with early stage ones. According to Callon (1994), the rationale for public intervention in science policy is to maintain a high level of diversity in order to avoid early lock-in on specific technological solutions. In the biotech model, public investment in academic research and in stimulating start-up creation is indeed useful in generating a diversity of technological development opportunities, and thus remedying market failure. However, such investment efforts may turn out to be less effective as alliances and internal architectural competencies can be substituted. Our research shows that those having the highest capability to benefit from the exploration of technological knowledge are the large centralized pharmaceutical firms: arguably assisting these firms is neither necessary nor encourages diversity. In contrast, public policies may encourage more alliances at the commercialization stages, when the big pharmaceutical firms have complementary assets and rich marketing experiences that NBFs and academic organizations lack.

This study has clear managerial implications. For managers in big incumbents our findings justify the long-term strategic investment in new technology territories. It shows that a broad knowledge base may create more chances to enter into and gain benefits from alliances. An alternative way to achieve the same target, according to this study, is that managers organize R&D activities under more centralized planning and control. In addition, the substitution effect between knowledge breadth and R&D centrality, and the negative impact of knowledge concentration on alliance formation indicate some of the potential dangers of using alliances. As recognized by many managers, forming an alliance with a partner for the short term gain of a

single product coming speedily to market may not be worth the trouble if there is a serious danger that the long-term knowledge position will be undermined. In situation where such dangers are serious, an alternative method is to concentrate resources on one or a few technological knowledge areas and strengthen firm in-house development capabilities. Finally, managers can consider using alliances as real options, but they need sufficient architectural knowledge to improve the competence in monitoring market change, crafting option contracts and exercising option opportunities.

7. Limitations and future directions

Our work is inevitably limited by several considerations. First of all, this research focused on alliance formation and did not take a nuanced look at the performance of each firm/alliance in terms of drug development outcomes and the like. So we need to be cautious in drawing on the implications of our findings in predicting firm/alliance performance or success. Second, and importantly we took a technologically biased view of knowledge, which we measured using patent classes. Obviously, this approach has the advantage of objectivity and robustness. But it does not capture many important and more tacit dimensions of knowledge capability. Whilst one could argue that the tacit dimension is probably correlated with the patenting, one cannot be sure of this. Third, our modeling did not look at network effects in the biotech industry, where knowledge is transmitted not only via alliances directly, but also by making alliances with firms that have alliances with other partners.

There are many researchers working in this field and we anticipate future work following several tracks. One is to investigate in more depth the influence of knowledge base features and organization structure on the new drug development of incumbent *firms* (as has been pioneered

by Rothaermel and Deeds, 2004). This would allow us to see if there is symmetry between external absorptive capacity and internal capability. Another theme is to examine the impact of *alliance projects* on research outcomes. It would be useful to see how many of the alliances achieve their objectives (see for instance the work of Hoang and Rothaermel, 2005). Such research would also test the ideas of relative absorptive capacity of alliance partners as laid out by Lane and Lubatkin (1998).

Another direction for future work would be to expand our measures of knowledge breadth beyond those provided by patents, by looking at other dimensions of capability. In this vein of reasoning, we recognize that knowledge lies beyond any dyadic alliance. There is potential to utilize network analysis to capture the position of the large firms in the alliance-making field and shed further insight into the path-dependent feature of alliance formation (see for instance Hagedoorn's work). Finally, future research can apply our framework to, and test it on, other industries, such as telecoms and semiconductors, to see how rapid innovation in the industrial environment influences the incumbents' collaboration activities.

In sum, this study explores how the firm's knowledge base and knowledge management in terms of R&D organization structure influence its propensity to use alliances in exploring technological development or in exploiting business opportunities. By doing this it sheds light on our understanding of absorptive capacity and the related concept of dynamic capabilities. In this new century, the development of knowledge economies requires firms to have superior innovation capabilities. Because "the ability to exploit external knowledge will be the critical component of innovative capabilities" (Cohen and Levinthal, 1990, p. 128), we hope that this study will help to reinvigorate the exploration of how to build up innovation capabilities across the boundary of the firms.

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Table 1
Descriptive analysis and correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. # of new alliances $_{t}$	1.00													
2. Concentration of knowledge	0.19*	1.00												
3. R&D intensity (1 000US$)	-0.13	0.04	1.00											
4. Size	0.29*	0.01	-0.20*	1.00										
5. EBIT (billion US$)	0.32*	0.00	0.05	0.35*										
6. Europe	-0.14	0.15	-0.20*	0.43*	-0.07	1.00								
7. # of new alliances $_{t-1}$	0.52*	0.19*	-0.22*	0.35*	0.25*	-0.28*	1.00							
8. Breadth of knowledge	0.27*	-0.05	0.00	0.44*	0.29*	0.18*	0.25*	1.00						
9. Centrality scale	0.33*	0.16	0.15	0.13	0.10	-0.16	0.22*	0.15	1.00					
10. Decentralized	-0.08	-0.01	-0.05	-0.04	-0.07	-0.10	-0.17*	-0.14	-0.65*	1.00				
11. Decentralized-hybrid	-0.10	-0.01	-0.05	-0.04	-0.06	-0.09	-0.11	-0.12	-0.32*	-0.12	1.00			
12. Balanced-hybrid	-0.02	-0.00	-0.01	-0.01	-0.00	-0.06	-0.03	-0.06	-0.19*	-0.16	-0.14	1.00		
13. Centralized-hybrid	0.11	0.07	0.00	0.01	0.05	0.00	0.01	0.03	0.25*	-0.33*	-0.28*	-0.34*	1.00	
14. Centralized	0.20*	0.15	0.13	0.15	0.18*	0.19*	0.21*	0.18*	0.67*	-0.23*	-0.22*	-0.30*	-0.51*	1.00
Mean	4.37	2.57	1.21	10.21	1.03	0.28	4.16	16.21	3.72	0.16	0.10	0.18	0.38	0.18
S.D.	5.21	3.64	2.11	1.93	0.54	0.34	5.17	5.72	1.18	0.42	0.33	0.41	0.45	0.42

* $p<0.01$

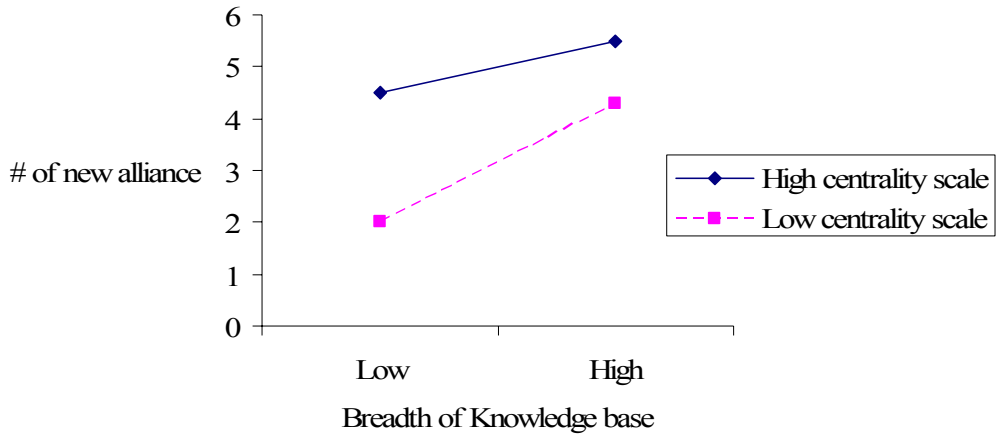
Table 2
Negative binomial regression on the number of new alliances with fixed-year effects [a, b]

	Model 1	Model 2	Model 3
Controls			
Concentration of knowledge	-0.264* [0.123]	-0.324* [0.130]	-0.348* [0.142]
Later-stage alliances	0.723+ [0.422]	0.649 [0.437]	0.522 [0.383]
R&D intensity $_{t-1}$	0.311 [0.215]	0.286 [0.189]	0.265 [0.179]
Size $_{t-1}$	0.314** [0.059]	0.275** [0.057]	0.299** [0.055]
EBIT $_{t-1}$	0.121** [0.015]	0.124** [0.017]	0.119** [0.015]
Europe	-0.220 [0.138]	-0.254 [0.157]	-0.204 [0.136]
Y $_{t-1}$	0.367** [0.023]	0.405** [0.027]	0.366** [0.038]
Predictors			
Breadth $_{t-1}$		0.145** [0.028]	0.178** [0.046]
Centrality Scale		0.207** [0.036]	
Decentralized-hybrid			-0.429 [0.254]
Balanced-hybrid			0.186* [0.085]
Centralized-hybrid			0.486** [0.175]
Centralized			0.790** [0.197]
Breadth $_{t-1}$ * Centrality scale		-0.069** [0.012]	
Breadth $_{t-1}$ * decentralized-hybrid			-0.019 [0.013]
Breadth $_{t-1}$ * balanced-hybrid			-0.079** [0.020]
Breadth $_{t-1}$ * centralized-hybrid			-0.094** [0.029]
Breadth $_{t-1}$ * centralized			-0.118** [0.017]
Wald χ^2	307.84**	369.63**	397.32**
$\Delta\chi^2$ [c.]		61.79**	89.48**

[a.] S.E. in brackets
[b.] In all models year dummies were included.
[c.] Represents statistical comparison with base model 1.

+ $p < 0.10$
* $p < 0.05$
** $p < 0.01$

Figure 1
Split-plot analysis of the interactive effects of R&D organization structure and knowledge breadth on alliance formation



Appendix I
Derwent Biotechnology Abstracts Technological classes and Sub-classes

DBA Technology Classes	DBA Technology Sub-Classes
A-Genetic-Engineering-and-Fermentation	A1-Nucleic-Acid-Technology
	A2-Fermentation
B-Engineering	B1-Biochemical-Engineering
C-Analysis	C1-Sensors-and-Analysis
D-Pharmaceuticals	D1-Antibiotics
	D2-Hormones
	D3-Peptides-and-Proteins
	D4-Vaccines
	D5-Other-Pharmaceuticals
	D6-Antibodies
	D7-Clinical-Genetic-Techniques
E-Agriculture	E1-Biological-Control-Agents
	E2-Plant-Genetic-Engineering
	E3-Pesticides
	E4-In-Vitro-Propagation
	E5-Agricultural,-Other
F-Food	F1-Food-and-Food-Additives
G-Fuels,-Mining-and-Metal-Recovery	G1-Biofuels-and-Solvents
	G2-Mining-and-Metal-Recovery
H-Other-Chemicals	H1-Polymers
	H2-Chiral-Compounds
	H3-Miscellaneous-Compounds
	H4-Polyunsaturates
J-Cell-Culture	J1-Animal-Cell-Culture
	J2-Plant-Cell-Culture
K-Biocatalysis	K1-Isolation-and-Characterization
	K2-Application
L-Purification	L1-Downstream-Processing
M-Waste-Disposal-and-the-Environment	M1-Industrial-Waste-Disposal
	M2-Environmental-Biotechnology