Alliance formation propensity in a global industry network

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Abstract: What factors determine which firms in an industry ally with each other? This paper analyses a sample of 497 alliances, in ten countries, in the global pharmaceutical sector where alliances are prolific and central to corporate strategy. The results suggest that direct technological commonality (measured by cross patent citations between each pair), indirect commonality (measured by the degree to which they share common third-party technology sources), and prior alliance ties statistically explain the propensity that any two firms in a network will form an alliance. We also explore cross-border effects to see if companies originating in different nations are more likely, or less likely, to form alliances because of their national origins.

Keywords: alliance formation; networks; global pharmaceutical industry; patent citations.

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1 Introduction: who allies, and why?

In an industry consisting of hundreds or thousands of firms worldwide, what explains a firm's propensity to form an alliance with one particular partner? Alliances, which proliferate today, involve a range of cooperative joint activities between two or more companies, from co-marketing arrangements, to licensing of intellectual property, to outsourced or joint manufacturing, to joint R&D efforts. Alliances can be contractual or involve the creation of a third joint venture company by the two principals. Alliances confer several advantages such as access to new knowledge which is often more complex and nuanced than can be obtained via markets or hierarchies (Podolny and Page, 1998). However, alliances may also involve significant uncertainty about future costs and benefits because of the possibility of opportunistic behaviour and potential competition from a partner (Park and Zhou, 2005). Nevertheless, the proliferation of alliances suggests that, despite the negative aspects of alliances, companies consider them an indispensable strategic tool because the advantages outweigh the drawbacks and risks.

Whether two companies in an industry will form an alliance depends, in part, on the characteristics of each firm or partner. The bulk of past alliance research has taken the firm, or dyad, as the unit of analysis and looked at each prospective alliance partner's resources and capabilities to assess the likelihood of their forming an alliance (e.g., Levinthal and Fichman, 1988; Kogut, 1988; Geringer, 1991; Eisenhardt and Schoonhoven, 1996).

However, later studies such as Gulati (1995, 1999) and Stuart (1998) added a network perspective by suggesting that a firm's propensity to undertake alliances will also depend on its position in an industry network. A firm's propensity to ally with a particular partner (out of sometime thousands of companies in an industry) is therefore determined not only by each firm's characteristics but also the firm's position in relation to others in the industry network. A network approach is therefore a useful methodological tool for the study of alliance formation (Gulati and Gargiulo, 1999).

This is especially important in rapidly evolving sectors. Information about each company's capabilities, reputation, and knowledge, flows not just directly between firms but also indirectly via the network or third parties (Nohria, 1992). Alliance ties, and the network links a firm can form, constitute a quicker route to accessing resources externally and thus altering the strategic structure or position of the firm (Ahuja, 2000; Gimeno, 2004). A firm's position can be mapped in several different ways: e.g., network maps of alliance ties with other companies (e.g., Gulati, 1999); or geographical proximity to other firms with country labels (Spencer, 2003); or the social ties of employees and their mobility between companies (Rosenkopf and Almeida, 2003); or maps of technological commonality between companies based on their patent citations (Stuart and Podolny, 1996; Mowery et al., 1998). Each of these network maps can show a very different position and linkages for each firm.

1.1 Predicting alliance formation by mapping a firm's position in technological and prior alliance ties networks in the global industry

This study plots the network links of over 100 companies, in ten nations, in the pharmaceutical sector, over an 11-year period. It is one of the few to *simultaneously* map two networks, the network of technology commonalities as well as the network of alliance ties, to examine alliance formation propensity.

- *Network map of patent citations:* Technology commonalities between any two pairs of firms are tracked by analysing their patent filings. Each patent application typically cites other prior patents registered by other companies, and this can be used to track knowledge flows and knowledge spillovers (Jaffe and Trajtenberg, 2002). Here, we track the 'cross-citations' of patents across every pair of firms in the sample, as well as their citation of common third-party patents in order to construct a measure of technological commonality which can be used to gauge the propensity to form an alliance. (Please see the Appendix and Table 1 for further details.)
- *Network map of prior alliance relationships:* This study also plots a second, *very different*, network map for all the firms, which traces their prior alliance (or inter-organisational) ties to see if past alliance relationships influence the likelihood of future additional alliance formation between them in a subsequent time period.

  For the same industry and firms, the two networks turn out to be generally very different, and provide alternate explanations. (The Appendix shows how the two network maps, for the same set of companies, are quite different.) Simultaneously, considering past relational and technological effects should therefore provide a richer explanation for the likelihood of alliance formation.
- *Cross-border or country of origin effects:* A third feature of this study is a discussion and testing of 'cross-border' or partner location effects, to see how the nationality of an alliance partner affects the propensity of alliance formation. Specifically, we ask whether the technology-alliance network interaction effects are accelerated or dampened when two prospective partners are from same country or region.

In this paper, we are also interested in the *interaction* between technology commonality (e.g., Stuart and Podolny, 1996) and alliance ties (Ahuja, 2000). Koza and Lewin (1998) argued that inter-organisational ties and firm capabilities co-evolve in interaction. But this has not been tested empirically in previous studies (Gulati, 1999). Given the increasing importance of alliances as vehicles for learning and capability building (Powell et al., 1996; Rosenkopf and Almeida, 2003), the interaction between these two networks is a gap which this paper hopes to fill.

This paper is organised as follows: theory and hypotheses are developed for the three groups of variables

- cross-border effects
- technology commonality
- alliance ties.

Next, we describe the two secondary datasets which were blended to derive our sample. This is followed by sections on methodology, testing and results, ending with conclusions for scholarship and alliance practice.

2 Theory and hypotheses

A company's decision to form an alliance (and with whom) is partially influenced by

- the need to access technologies that the firm does not possess (Mowery et al., 1998)
- history of past inter-organisational ties (Gulati and Gargiulo, 1999).

This, in turn, is affected by the country of origin of each prospective partner. On the one hand, the likelihood of finding novel ideas may be greater outside the nation of the firm. On the other hand, the fact that the knowledge is embedded in a foreign organisation and environment makes the absorption of such knowledge more difficult, and managing the alliance relationship more difficult. Because developing a new relationship is arduous, and because alliances can sometimes be hazardous (because of opportunistic misbehaviour of partners, or later competition from them, or in dedicated assets that may be rendered useless if the alliance were terminated), firms often prefer stable relationships characterised by trust and rich exchange of information with known partners (Levinthal and Fichman, 1988). Over time, these 'embedded' relationships (Granovetter, 1985) become a repository of information on the availability, capability, and reliability of current and potential partners (Kogut et al., 1992). According to some studies, alliance formation is path-dependent, in the sense that prior technical and inter-organisational linkages determine how the future ties evolve (Duysters and Lemmens, 2003).

In summary, this paper investigates the tension between two contrary strategic drivers for alliance formation:

- the desire to seek new ideas, knowledge and capabilities (which are sometimes more novel and more valuable, as far as the firm is concerned, when derived from foreign partners), versus
- the greater transaction costs, risk and knowledge absorption difficulties in allying with far away, or less-familiar partners.

This study's coverage of 11 years provides some longitudinal or historical perspectives, to assess how alliance partner selection is shaped by both technological commonalities, past inter-organisational ties, and cross-border or nationality labels.

2.1 Cross-border effects

Is a prospective alliance partner more attractive, or less attractive, if based in a foreign country? Does 'foreignness' enhance or dampen the likelihood of alliance formation. Our global industry network comprising of US, Japanese and European firms allows us to explore this question.

The literature does not provide any unequivocal answers. There appear to be contrary pulls between

- the desire to access novel foreign knowledge available through foreign alliance partners
- the greater caution a firm has when a prospective alliance partner is from a different country.

Even for giant multinationals such as IBM, a major motivator of foreign partnerships is the search for novel knowledge (Palmisano, 2006). In the bio-pharmaceutical area, disease vectors are different from one nation to another and different companies specialise in certain areas of medicine. Innovation in a range of key industries (such as bio-sciences, electronics, and telecommunications) is nowadays more widespread, over a larger set of countries than ever before (Mowery and Macher, 2007). There is an emerging shortage of scientific and engineering talent in several OECD nations (National Science Foundation, 2009). At the same time, the capabilities of technical personnel worldwide and in emerging nations has considerably improved (Florida, 2005). One manifestation of this is the greater R&D expenditures by multinational companies outside the home nation. According to National Science Foundation (2009) in 2004 the ratio of US pharmaceutical company R&D spending in their foreign affiliates divided by R&D expenditures at home in the USA was 17%. This ratio today may have exceeded 0.20. Another manifestation of this thirst for foreign ideas and talent is the escalation in foreign alliance relationships.

By bringing together two distinct country capabilities, international partners can learn from each other at a higher level than in domestic alliances (Ghoshal, 1987; Zahra et al., 2000). Complementarity and novelty of ideas also may be higher than in a domestic context. Besides technological learning, international alliances also upgrade a firm's general global business competitiveness (Dunning, 1995). Commercial success in pharmaceuticals is today increasingly driven by the need to amortise huge R&D outlays over a larger range of international markets. In order to increase the geographical scope of a drug's future sales, speedy clinical testing and certification need to be performed in many (if not all) foreign nations (Cockburn, 2004). This in turn requires local institutional knowledge about the medical establishment and links with local regulatory authorities – institutional knowledge which a foreign partner can provide.

The above arguments point towards foreign alliances being more desirable and valuable, compared to domestic alliances, *ceteris paribus*. But there are contrary and opposing views in the literature. Relationship building, blending of routines, and the inevitable ongoing negotiations between the managements of the allies, takes time in all alliances (Holcomb and Hitt, 2007). The time and cost of managing a cross-border and cross-cultural alliance relationship would be even greater. In foreign institutional environments, in an unfamiliar legal system, and where intellectual property protection is perceived to be weaker, these all constitute greater barriers and caveats to foreign alliance formation. According to some studies in Kale and Singh (2009), the termination rate of foreign alliances is high. The lack of familiarity between alliance partners from different countries produces a higher perceived risk of opportunism than exists in domestic alliances (Li et al., 2008).

In sum, the literature provides contrasting views: The greater desirability of foreign (as opposed to domestic) partners is set against the greater perceived risks and costs of foreign partnerships. What is the *overall* effect of these two contrary forces, one attracting and one repelling, on alliance formation propensity? In the absence of any scholarly consensus we propose two contrasting hypotheses:

H1a When prospective alliance partners originate in different nations, the likelihood of alliance formation is greater.

H1b When prospective alliance partners originate in different nations, the likelihood of alliance formation is lower.

2.2 Direct technology commonality

In searching for a prospective partner in an industry consisting of thousands of companies, firms tend to look for those with knowledge somewhat close to their existing knowledge base, according to Cohen and Levinthal (1990) or Eisenhardt and Schoonhoven (1996). Stuart's (1998) study supports the argument that alliances are more feasible and effective when the alliance partners' technological profiles are closer. But an alliance partner that provides *identical* knowledge, which a firm already has, is of no use. Neither firm will have much to learn from the other (Mowery et al., 1998). There would be no point in such an alliance. On the other hand, a prospective ally that has knowledge very far removed from a firm's existing knowledge base is also undesirable – since learning costs may prove too high and bridging the technological differences between the two companies' knowledge bases may produce no net synergistic benefit (Cantwell and Barrera, 1998). Some degree of technological differentiation combined with some degree of overlap may be optimal, we hypothesise. An *intermediate* position, between identical and completely different technology held by the two companies would allow for an understanding of the intricacies and applicability of the new knowledge an alliance partner can provide (Shenkar and Li, 1999).

In short, there are opposing strategic pulls, between the need for some overlap with a partner's knowledge so as to facilitate knowledge transfer, and the need for sufficiently distinct technologies in order for the prospective allies to have something to learn from each other (Rosenkopf and Almeida, 2003). In operationalisational terms, this means that the propensity to form an alliance is hypothesised to be an inverted U-shaped relationship.

H2 There is an inverted U-shape relationship between the propensity of two firms to form an alliance and their direct technology commonality.

2.3 Indirect technology commonality

The above hypothesis relates to direct technological commonality between the two firms (which we will measure by looking at how they have cited each others' patents). However, a firm's technology is also *indirectly* connected to *other* companies in a technology network through a common *external* knowledge pool. This will also influence the propensity of a particular pair of firms (or dyad) to form an alliance. While direct technological commonality is an indicator of the extent of technological overlap between two firms, indirect commonality captures the *breadth* or context of the two prospective allies' technological foundations shared through an external knowledge pool. In network analysis terminology, two firms are said to be 'structurally equivalent' when they have identical links to the same *third parties* (Wasserman and Faust, 1994). In a plot of patent citations, structural equivalence refers to firms that draw on a common third-party technology source.

It is possible that direct competitors may sometimes share the same body of third-party technology and (if worried about future competition) may not ally with each other. Other firms in an industry that do not directly compete may be more prone to doing so. However, in rapidly-evolving technology sectors one finds many cases of firms competing, while at the same time forming alliances with their competitors in specific applications if they feel that joining forces will speed up the innovation or learning processes (Hagedoorn, 2002).

Stuart (1998) showed that two structurally equivalent firms in the patent network are significantly more likely to form an alliance than a pair of firms that work in distinct technological areas. A common external technology pool creates better alliance opportunities because there is a larger pool of potential partners who share an understanding of technologies and organisational routines. Mowery et al. (1998) also reached a similar conclusion.

Therefore, firms that share the same external knowledge sources (i.e., they both cite the same third-party or body of knowledge) are hypothesised to be more likely to collaborate, hoping for potential synergy in broadly related technological inventions.

H3 The more two firms are linked by the same body of common *third-party* technology sources in a network, the greater the likelihood of them forming an alliance.

2.4 Direct alliance ties

We now turn from technological commonality between any two prospective alliance partners, to examining the history of their past alliance ties, since some literature asserts that past alliance ties increase the propensity that the two firm will form additional alliances.

Developing a new relationship takes time and an investment so that, once firms have developed a relationship, they prefer to persist in relying on this existing relationship. Firms that have worked together in the past will have basic understandings about each other's skills and capabilities (Heide and Miner, 1992), which provide an impetus for further collaboration and a base for inter-partner trust (Gulati, 1995).

The first place a company tends to search for external knowledge is from organisations surrounding it in the network of prior or existing inter-organisational ties (Gulati, 1995) in which the firm is embedded (Granovetter, 1985). As knowledge about partners increases, information asymmetries between partners decrease. Consequently, uncertainty about their behaviours decreases and trust builds between the partners – from the relational routines necessary to create a successful alliance (Dyer and Singh, 1998). As a result, firms experienced in prior alliance relationships can forgo the complex contractual provisions that would be necessary for partners working together for the first time. In short, the likelihood of a new alliance is greater with existing partners than with other companies.

Alliances vary in terms of the 'strength' of the tie between them. Some may only be a temporary co-marketing arrangement. Others may involve just a patent license. Joint manufacturing arrangements involve deeper and stronger ties, while a joint R&D programme or equity joint venture is generally considered the strongest type (Rowley et al., 2000; Contractor and Lorange, 1988). In this study, we measure the overall strength of the relationship between two alliance partners by an index (please see Table 1 for the construction of this and other variables) that covers both the number of alliances between them as well as the strength of the tie in each of their alliances.

Previous studies, such as Gulati (1995) have found that second-order (squared) terms, designed to capture non-linear effects, are significant. As the number and strength of alliances between two firms increases, further interactions provide incremental value and learning – but at a diminishing rate. In other words, the increment of learning from $(n + 1)^{th}$ alliance will be lower than the increment from the nth alliance between firms, until a considerable overlap in capability or knowledge eventually negates the need for any further collaboration. A saturation point is reached. Hence, the hypothesis that:

H4 There is an inverted U-shape relationship between the propensity of a pair of firms to ally and a composite index (combining the number and strength) of their prior alliance ties.

2.5 Indirect alliance ties

In an industry network, firms are also connected *indirectly* through other firms (Burt, 1992). For instance, a firm A seeking collaboration partners can obtain information about prospective partners from existing partners B as well as their partner's partners and so on. Information on a potential partner C's technology and reputation would be considered more reliable when received through an existing partner B.

Information flows can occur via third and fourth firms that are not necessarily directly allied. For example, in Appendix: Period 2, Chiron and BASF are not directly allied. However, information flows can occur through their common ally Hoechst or Ciba, forming an indirect network tie. Here, the perspective is on the 'structural' (or positional) aspect of the network, rather than on the direct ties between firms.

The network position of a particular firm may put it 'close' to another, even though there is no direct tie, as yet, between the two. Being close to each other in the network of prior alliances provides firms with second-hand information, which may enhance the likelihood of a new alliance (Gulati, 1999). We map the length of a path connecting two firms in a network via third firms. The rationale for a distance-weighted 'structural' measure is that the quality and quantity of information flow decreases, the longer the paths connecting two firms (Ahuja, 2000). This leads to the following hypothesis:

H5 The shorter the path connecting a pair of firms in a network, the higher the likelihood that they will ally with each other.

2.6 The interaction of alliance ties and technology commonality

Thus far, we have hypothesised the effects of alliance ties and technology commonality on new alliance formation. But how do these two *interact*?

Alliance learning is more than just the acquisition of knowledge and includes building the firm's capabilities for further action, in a process that Argyris and Schon (1978) called 'double loop learning'. Capabilities derive not only from resources, but also from the way in which these are combined and utilised in a set of organisational routines (Nelson and Winter, 1982). Therefore, if a firm is to learn effectively from alliances, a shift or convergence towards compatible routines with partners is important. This may tend towards technological convergence (Stuart, 1998).

But over time, this technological convergence reduces the resource complementarity of the alliance and its subsequent ongoing value (Ring and Van de Ven, 1994). For instance, assuming that firms i and j want to undertake alliances, firm i will seek out firm j with related but still distinct knowledge profiles. But once they learn from each other, firms i and j will begin to look more alike. Hence, the existence of prior ties would make firm j less attractive as a partner for another alliance. In sum, as two firms' inter-organisational tie strengthens, their technological profiles become similar through alliance learning. Such technological convergence eventually negates the value of further collaboration (Baum et al., 2010).

Absorptive capacity facilitates technology learning and hence eventually technological convergence (Zhang and Baden-Fuller, 2010). Broadly speaking, our two main variables – (prior) alliance ties and technological commonality – represent two different forms of absorptive capacity in alliances. A common theme in previous alliance literature on absorptive capacity is that prior alliance ties (Gulati, 1995) and/or technological commonality (Stuart, 1998) ease knowledge transfer and learning. Prior alliance ties are concerned with partner-related uncertainty while technological commonality has to do with reducing task (i.e., learning)-related uncertainty. Here, we propose a possible substitution effect between partner learning and technology learning (Casciaro, 2003).

That is to say, if the reduction in partner uncertainty is the mechanism through which prior ties guide the formation of new ties, this effect should be weaker when there exists low uncertainty concerning technology learning. Note that although prior alliance ties can still have an absolute positive effect on the formation of new ties, over and above the effect of technological commonality, the marginal effect of prior ties is diminished. If so, the interaction between the two will be negative as far as likelihood of future or further alliance formation is concerned. Hence,

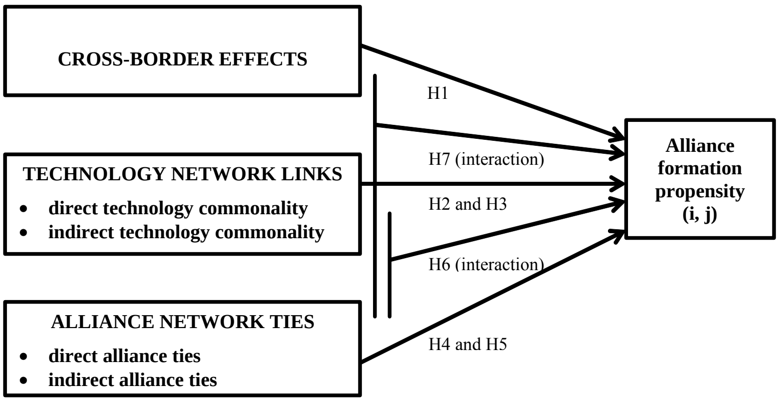
H6 A pair of firms' alliance ties and technology commonality will have a negative interacting effect on the probability of its alliance formation.

In terms of the interaction effect, whereby subsequent to alliance formation the partners learn from each other, and their technologies converge, if we propose that in international alliances there is a higher level of learning which accelerates technological convergence faster than in domestic alliances, then we hypothesise that:

H7 The negative interacting effect will be greater in international pairs than in domestic pairs.

Figure 1 summarises the hypotheses.

Figure 1 Operational model



3 Research design

3.1 Sample and data

The pharmaceutical industry is a highly dynamic sector, geographically dispersed worldwide. The sector encompasses DNA and molecular manipulation, as well as traditional empirical approaches to drug discovery. Pharmaceutical firms face strong pressures to develop medicines for a global market, and exploit economies of scale and scope at the global level (Halliday et al., 1997). The growing interdependence between previously discrete technologies makes it increasingly difficult for any single firm to stand alone (Henderson and Cockburn, 1996). Alliances ‘bridge’ disparate knowledge areas (Hsu and Lim, 2006; Stuart and Podolny, 1996), serve as a platform for recombining technologies in novel ways or in the case of biotech-pharma alliances, also rely on the certification and market introduction expertise of the larger of the alliance partners.

This study traces longitudinal panel data on alliance ties and technology commonality in the industry for 103 companies, in ten nations, across three regions, over an 11-year interval 1990–2000. It is one of the few that combines two databases, one on alliance formation and the other on patent citations. Data on alliance formation were drawn from the Securities Data Company (SDC) database where the listing of alliances prior to 1990 is very incomplete (Anand and Khanna, 2000). Taking *all* alliances by pharmaceutical-related firms (whose business portfolios include pharmaceutical operations) between 1990 and 2000 resulted in 5,484 alliances which constitute about 21.6% of 25,356 alliances in all manufacturing sectors during 1990 to 2000.

Patent data were obtained from CHI Research Inc, a research organisation that supplies patent indicators (Kotabe et al., 2007). The CHI database corrects for company re-naming due to mergers and acquisitions and spin-offs, etc., and reassigns patents accordingly – allowing one to trace patents despite company name and ownership changes. The CHI database covers 1,025 companies across manufacturing sectors (460 US and 565 non-US companies). Of the 1,025 companies, 315 are chemical and pharmaceutical firms.

All CHI data were then combined with SDC data. Because we needed complete panel data on both alliances and patents, the selection was restricted to alliances where both parent firms belonged to the CHI database; hence the number of firms was reduced to 103 from 315 firms. 103 principal firms were thus identified, based in ten nations over three regions – 36 firms in the USA, 42 in Japan and 25 in Europe.

3.2 Variables and measures

The final combined dataset covers 497 alliances between these 103 companies, over an 11-year time period (1990–2000), with values for each year. We use a one-year lead for the alliance formation variable with respect to explanatory variables. Please see Table 1 for variable definitions.

Table 1 Variables and predicted signs

Variable name	*Measurement*	*Prediction*
Alliance formation	Whether firms i and j entered an alliance or not	Dependent variable
Cross-border variable	Set to 1 if firms in a dyad have different national origins and 0 if they have the same national origin.	'Cross-border effects'
Technology network links	((Cross citations + Citations to common third parties) / Total citations), for a given pair of firms i and j.	
Direct technology commonality	(Cross citations / Total citations), for a given pair of firms i and j.	+/− (inverted U) 'relative absorptive capacity'
Indirect technology commonality	(Citations to common third parties / Total citations), excluding firm i and firm j's cross citations.	+ 'structural equivalence – sharing common technology pools'
Alliance network ties	Distance weighted alliance ties, i.e., Proximity(i, j) = (N – 1)/No. of steps (i, j), where N is the maximum number of steps.	
Direct alliance ties	Weighted prior ties = Number of prior alliances between firms i and j in the previous year, weighted by the strength of each tie as (JV = 5, joint R&D project = 4, manufacturing agreement = 3, licensing = 2, marketing agreement = 1).*	+/− (inverted U) 'learning and relational benefits'
Indirect alliance ties	The measure of indirect ties is the interaction of proximity measure and the dummy variable (1 = no direct tie and 0 = direct tie) so that it captures only the indirect 'structural' component.	+ 'informational benefits – reference and control'
Alliance experience, Firm i	The total number of alliances firm i had had previous to the current year.	Control variable
Alliance experience, Firm j	The total number of alliances firm j had had previous to the current year.	Control variable
Subsector-type dummy	Set to 1 if firms in a dyad belong to different sub-types and 0 if they belong to the same sub-type.	Control variable

Note: *In the event that more than one type of arrangement was present in a single alliance, that alliance was given a weight corresponding to the highest out of the multiple categories presented.

3.3 Measurement of the dependent variable

- *Alliance formation:* The dependent variable tracks alliance activity, or alliance formation between firms i and j. If a pair of firms enters into at least one alliance in a given year, it is given a value of 1, and 0 otherwise.

3.4 Measurement of explanatory variables

When filing patents, companies tend to cite, in their patent application, their own as well as other companies' prior work. We call these 'patent citations'. Patent citations are indicators of technological sources and antecedents. Admittedly, there are limitations in patent indicators. For example, the propensity to patent varies across technologies, firms and industries. Patents represent codified knowledge and not tacit know-how. Patent examiners also add their own citations (Alcacer and Gittelman, 2006). While recognising these usual limitations, it is nevertheless generally accepted that citations provide a useful metric, especially in patent-intensive sectors such as pharmaceuticals. In our study, patents and patent citations are aggregated at the firm level. Thus, a high degree of citations between firms suggests that these firms overlap in the technological foundation for a specific application.

When filing a patent application, a company 'i' will cite in its patent application existing patents held by

a their own company

b a prospective alliance partner 'j' as well as

c third-party (i.e., yet other companies') patents.

One can therefore compute ratios as follows.

- *Direct technology commonality*: Similarly to Mowery et al. (1998), a cross-citation ratio between firms i and j was calculated as ((Firm j's patents cited by Firm i's patents + Firm i's patents cited by Firm j's patents) / Total Firms i and j's citations). The cross-citation ratio measures the level of direct technological commonality between firms i and j. Given our prediction of an inverted U-shaped relationship, we used both first (linear) and second-order (squared) terms in our analysis. However, to reduce possible multi-collinearity, we used the square of the deviation from the mean.
- *Indirect technology commonality*: The extent to which two firms share common technology sources is measured as ((Citations in Firm i's patents to the third-parties also cited in Firm j's patents + Citations in Firm j's patents to the third-parties also cited in Firm i's patents) / Total Firms i and j's citations). Since this construct specifically *excludes* firm i and firm j's own cross citations, this variable measures the degree to which firms i and j draw from the same *external* or third-party technology pool.
- *Technology network links* encompass both cross and common citations, as measured by ((Cross citations + Citations to common third-parties) / Total citations).

  To compute alliance tie variables, we constructed a binary adjacency matrix where 1 indicates the presence of an alliance, and 0 its absence. The matrix was inputted into

UCINET V a software that allows the computation of various network measures. The minimum number of 'steps' or paths required to connect firms i and j in the network was counted. This 'distance' measure was then inverted to a 'proximity' measure, i.e., $\text{Proximity}_{(i,j)} = (N - 1)/d_{(i,j)}$, where N is the largest possible distance and the denominator is the minimum number of 'steps' that connects firms i and j (Borgatti et al., 1999). We decomposed the proximity measure (or the measure of *alliance network ties*) into direct and indirect ties. Direct alliance ties measure the 'relational' strength of the direct tie/s between firms i and j whereas indirect ties measure the 'structural' proximity of a pair of firms through third-parties.

- *Direct alliance ties:* Simply counting the number of alliances between two firms is easy, but one cannot then differentiate between strong and weak alliances. Our measure of direct alliance ties is a weighted index that combines both the number of the alliance ties as well as the strength of each tie between any pair of firms i and j. The weighting scheme assigns a higher weight for stronger governance forms and greater interfirm interaction, ranging from 1 (for simple co-marketing arrangements) to 5 (for equity joint ventures). This is in line with previous weighting schemes by Gulati (1995) and Rowley et al. (2000). We hypothesised that a negative returns phenomenon sets in for this variable. The quadratic term of direct ties is represented by cross products of the deviation from the mean.
- *Indirect alliance ties:* This variable measures network proximity between firms i and j – connected through *other* firms in a network. Our measure of indirect ties is the interaction of the proximity measure, i.e., $(N - 1)/d_{(i,j)}$ and a dummy variable (1 = no direct tie and 0 = direct tie). In this way the interaction term captures only the indirect 'structural' component, separately from the direct tie component.
- *Cross-border variable:* We test for cross-border effects by including a variable whose value = 1 for a pair of firms originating in different nations, and 0 for a pair of firms in the same nation. The question is, "Will the fact that prospective allies are based in two different nations reinforce or reduce alliance formation propensity and the technology-alliance interaction effect?"
- *Control variables:* A subsector dummy was introduced. The sample firms consist of four sub-types: health care (health care, medical equipment and supplies), pharmaceuticals (drugs and medicines) and biotechnology companies (focused only on biotechnology operations) and organic or inorganic chemicals. The subsector-type dummy was coded 1 if firms in a dyad belonged to different types or subsectors, and 0 if they belonged to the same type. Firm-type group membership may have contrasting implications. Firms in the same group tend to have similar or compatible operating systems and practices, making it easier to evaluate, communicate, and coordinate their cooperative activities (Lane and Lubatkin, 1998). But firms in the same group are also likely to manifest the same strategic scope and, thus, compete for the same market and products (Park and Ungson, 1997).

Including the frequency of occurrence of a focal event is a common method of controlling for unobserved heterogeneity (Heckman and Borjas, 1980). We counted the total number of alliances in each firm for each year and used the alliance number for each firm to control for firm-level heterogeneity that produce variance in a firm's ability or opportunity to collaborate.

Patent self-citations were calculated as the ratio of the number of self-citations to the total number of citations by each firm, and then pooled for the dyad (firms i and j). A high self citation ratio is an indication that a company is more prone to self-reference its own, rather than external technology, and more likely to persist in the same technological trajectory. 'Path dependence' is defined as the tendency for firms to persist in their own technology path or trajectory (Sorensen and Stuart, 2000). Path dependence is said to impede receptivity to external knowledge (Rosenkopf and Nerkar, 2001).

3.5 Methodology

The analysis utilises a random-effects probit model using alliance formation propensity as the dependent variable. With 103 companies, the maximum number of theoretically possible alliance formation events is therefore (103)(102)/2 = 5253. Over 11 years, but with only ten years usable, the number of observations is therefore (5,253)(10) = 52,530. As a methodological caveat, in such statistical analyses, by including all theoretical potential alliance combinations where several pairs of firms will never form an alliance, there is a danger of overstating the theoretical probability of zero. But this is not a concern in our dataset since the sample (and the network boundary) was defined by firms that had established at least one alliance during the time period 1990–2000.

Like firm-level unobserved heterogeneity, there is also the issue of dyad-level unobserved heterogeneity – especially when panel data are analysed. Random-effects models treat this issue by allowing error terms across years to be correlated and generate a coefficient, *Rho*, which indicates the extent to which unobserved differences across a pair of firms are found and corrected by the model (Gulati, 1999).

The random effects panel probit model is represented as:

$$\Pr\left(Y_{ij,t}+1=1\right)=F\left(a+bX_{ij,t}+cD_{ij}+U_{ij}\right) \text{ where } ij=1,\ldots,5,253;\ t=1,\ldots,10$$

$\Pr(Y_{ij,\,t}+1=1)$ is the probability of an alliance between firms i and j at time t + 1; $X_{ij,\,t}$ is a vector of time-varying independent variables that represent attributes of each dyad; D_{ij} is a time-constant vector of dummy variables characterising firms i and j in a dyad; U_{ij} are unobserved time-constant effects not captured by the variables; a, b and c are coefficients to be estimated; F represents the cumulative normal probability function. We can interpret the probability $\Pr(Y_{ij,\,t}+1=1)$ as an estimate of the conditional probability that a pair of firms will enter an alliance, given the attributes of a dyad.

4 Results and discussion

Table 2 reports the means, standard deviations and correlations for the variables. The correlation matrix has low coefficients. Exceptions are two variables involving the squared term, whose coefficients in two cases are 0.71 and 0.85. Hence, we checked for multi-collinearity by calculating the variance inflation factor (VIF) for Model 5 in Table 3. The test showed low and tolerable levels of multi-collinearity, with the highest being between the direct ties variable and the squared term of it (VIFs of 3.88 and 3.84 respectively), which is still statistically acceptable and below the threshold proposed by Neter et al. (1996).

Table 2 Descriptive statistics and correlation matrix

		Mean	*S.D.*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
1	Alliance formation	0.008	0.089	1.00										
2	Cross-border variable	0.707	0.454	–0.02	1.00									
3	Direct technology commonality	0.003	0.010	0.04	–0.05	1.00								
4	Direct technology commonality^2	0.0001	0.001	0.01	–0.03	0.71	1.00							
5	Indirect technology commonality	0.196	0.157	0.04	0.04	0.27	0.05	1.00						
6	Direct alliance ties	0.034	0.423	0.07	-0.02	0.03	0.002	0.03	1.00					
7	Direct alliance ties^2	0.179	3.196	0.04	-0.02	0.02	0.001	0.01	0.85	1.00				
8	Indirect alliance ties	2.881	7.482	0.01	0.01	0.03	0.01	0.02	–0.03	–0.02	1.00			
9	Path dependence	0.691	0.242	0.001	0.01	0.01	–0.01	–0.10	0.01	0.01	0.03	1.00		
10	Alliance experience, Firm i	3.953	4.754	0.04	0.11	0.11	0.02	0.16	0.08	0.06	0.25	0.10	1.00	
11	Alliance experience, Firm j	3.755	4.670	0.05	0.07	0.10	0.02	0.18	0.09	0.07	0.24	0.08	0.11	1.00
12	Subsector-type dummy	0.632	0.482	–0.04	0.08	–0.10	–0.01	–0.09	–0.05	–0.03	–0.02	0.02	–0.03	–0.01

Note: All independent variables are lagged by one year.

Table 3 presents the random-effects panel probit estimations. Model 1 is the baseline model including only control variables plus cross-border variable. Other independent variables are entered sequentially in subsequent Models 2 through 5. If adding a variable does not drastically alter previously introduced coefficients in sign or size, then we can conclude that the overall model is stable, and that adding more variables is desirable, especially if the overall explanatory power of the model is improved. Model 2 adds the direct technology commonality variables. Model 3 adds the indirect technology commonality variable. Models 4 and 5 include these plus alliance tie variables.

Table 3 Random effects panel probit estimates of alliance formation rate (H1 to H4)

	1	*2*	*3*	*4*	*5*
Direct technology commonality		20.827***	17.364***	17.089***	17.082***
		(3.754)	(4.124)	(4.130)	(4.145)
Direct technology commonality^2		–191.78**	–150.67*	–147.90*	–147.37
		(67.811)	(73.024)	(72.684)	(73.577)
Indirect technology commonality			0.422**	0.412**	0.405**
			(0.157)	(0.155)	(0.155)
Direct alliance ties				0.100$^\Psi$	0.096$^\Psi$
				(0.052)	(0.053)
Direct alliance ties^2				–0.009	–0.009
				(0.007)	(0.007)
Indirect alliance ties					–0.001
					(0.002)
Cross-border variable	–0.320***	–0.301***	–0.314***	–0.302***	–0.304***
	(0.050)	(0.050)	(0.051)	(0.050)	(0.051)
Path dependence	–0.118	–0.147	–0.102	–0.098	–0.100
	(0.106)	(0.105)	(0.106)	(0.104)	(0.104)
Alliance experience, Firm i	0.026***	0.022***	0.021***	0.020***	0.021***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Alliance experience, Firm j	0.031***	0.028***	0.026***	0.025***	0.026***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Subsector-type dummy	–0.413***	–0.363***	–0.364***	–0.352***	–0.353***
	(0.049)	(0.049)	(0.049)	(0.048)	(0.048)
Constant	–2.536***	–2.590***	–2.687***	–2.648***	–2.645***
	(0.092)	(0.094)	(0.100)	(0.098)	(0.098)
Rho	0.236***	0.222***	0.225***	0.196***	0.196***
	(0.030)	(0.029)	(0.029)	(0.031)	(0.031)
N. of observations	52,530	52,530	52,530	52,530	52,530
Log-likelihood	–2,245.10	–2,219.67	–2,215.65	–2,213.50	–2,213.30

Notes: $^\Psi p < 0.1$, $^*p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$. Standard errors in parentheses.

All models have the χ^2 statistics significant at better the 0.001. The χ^2 statistics (with d.f. = 1) were computed by comparing the log-likelihood of the restricted 'binomial probit model' with the 'random effects binary probit model'. The significant χ^2 statistics, together with the significant *Rho* across all models, suggest that unobserved time-variant heterogeneity at the dyad level is accounted for by the random effects probit model. The gradual improvement of log-likelihood functions throughout Models 1 to 5 suggest a better-fitting model as the technology and alliance variables are added.

In Model 1, H1b is supported. The negative and significant coefficient for the cross-border dummy suggests that alliance formation is more likely when the firms are from the same nation (as opposed to cross-border alliances). The positive and significant coefficient for each firm's prior history of alliances shows that alliance propensity is higher for firms that have accumulated a greater level of alliance history. Results also show that alliances are more likely to be formed by firms within the same subsector-type. The path dependence variable was not significant.

Hypotheses H2 to H5 were tested in Models 2 through 5. As predicted, the likelihood that a pair of firms will form another alliance is positively related to their direct technology commonality (measured by their patent cross citations) and negatively related to the second order (squared) term of technology commonality, with both effects significant at 0.001 and 0.05 level, respectively. Results for the squared term indicate that there may be a saturation point, i.e., a diminishing and eventually negative returns phenomenon for the direct technology commonalities of a dyad. Hence, H2 is supported. The indirect technology commonality variable, measuring the breadth of the common knowledge pool at the network level, has a positive and significant coefficient, supporting hypothesis H3. Partner choice is not only a function of the direct technology commonalities in a dyad, but also depends on the sharing of common third-party technology sources in a network.

The direct prior ties variable, valuing the strength of prior ties between firms i and j, produces mixed results. H4 is partially supported. The variable is positively related (*albeit* marginally) to alliance propensity. Through repeated alliances, firms learn about each other, develop relational norms around mutual understanding (Dyer and Singh, 1998), and generate an initial base of inter-partner trust (Gulati, 1995). However, the second order term of this variable is not significant and offers no support for the hypothesis of a curvilinear or 'diminishing returns' relationship. There could be several explanations. It is possible that the negative returns effect exists, but sets in at higher levels, with a number of alliances (per partner pair) that exceeds the numbers in our sample. Hypothesis H5 suggested that firms that were 'near' to each other in a network would be more likely to ally, *ceteris paribus*. But this was not supported in our results. The choice of partners was not statistically related to network proximity. Perhaps, proximity can help in searching for partners, but then not prove decisive in the final negotiation and selection of a partner (Rangan, 2000).

Since the interaction is hypothesised to occur at the network level (see Figure 1), we interacted the combined measure of technology commonality (i.e., technology network links) with that of alliance ties (i.e., alliance network ties). Table 4 provides the estimate results for the interaction effect with a cross-border context as moderator.

Table 4 Estimates for interaction effects with cross-border as contextual variable (H5 and H6)

	1 (complete set)	*2 (complete set)*	*3 (complete set)*	*4 (international pairs)*	*5 (domestic pairs)*
Technology network links		0.734***	0.778***	1.063***	0.409*
		(0.138)	(0.138)	(0.187)	(0.204)
Alliance network ties		0.002*	0.003**	0.002^{Ψ}	0.004*
		(0.001)	(0.001)	(0.001)	(0.002)
Technology network links × Alliance network ties			–0.011*	–0.021**	0.001
			(0.005)	(0.007)	(0.007)
Cross-border variable	–0.320***	–0.324***	–0.323***		
	(0.050)	(0.051)	(0.051)		
Path dependence	–0.118	–0.039	–0.035	0.141	–0.191
	(0.106)	(0.104)	(0.105)	(0.148)	(0.148)
Alliance experience, Firm i	0.026***	0.021***	0.021***	0.021***	0.023**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.008)
Alliance experience, Firm j	0.031***	0.026***	0.026***	0.027***	0.023**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)
Subsector-type dummy	–0.413***	–0.388***	–0.387***	–0.337***	–0.447***
	(0.049)	(0.047)	(0.048)	(0.063)	(0.074)
Constant	–2.536***	–2.693***	–2.710***	–3.285***	–2.450***
	(0.092)	(0.097)	(0.097)	(0.146)	(0.136)
Rho	0.236***	0.208***	0.207***	0.222***	0.173***
	(0.030)	(0.030)	(0.030)	(0.039)	(0.051)
N. of observations	52,530	52,530	52,530	37,180	15,350
Log-likelihood	–2,245.10	–2,228.96	–2,226.69	–1,303.67	–915.99

Model 1 is the baseline model. Model 2 introduces the technology links and alliance ties variables. Model 3 adds the interaction term to test hypothesis H6 which predicts the negative interacting effect between technology and alliance variables. We predicted that alliance ties and technology commonality on their own have a positive impact on alliance formation, but that the collective impact of the two is smaller than the sum of each. This should yield a significant and negative coefficient for the interaction term between the two variables. Indeed, the interaction term is negative and significant (p < 0.05), indicating that there is a diminishing likelihood of alliance formation between firms already connected in an alliance network if they have already developed a certain level of technology commonality. Adding the interaction term improves the model fit. Comparing log likelihood statistics of Model 2 with that of Model 3 there is an improvement in log likelihood = 2.27. [We tested improvement in fit as a chi-square statistics with d.f. = 1 ($\chi^2 = 2 * 2.27$; $p < .05$).]

In Models 4 and 5, we looked at the results for the different dyad sub-groupings (international pairs vs. domestic pairs) to test hypothesis H7. While the negative interacting effect is replicated and strengthened for international pairs (Model 4), the (–)

sign and significance of the interaction term disappears for domestic pairs. That is to say, the cross-border context reinforces the negative interaction effect on alliance formation propensity. An explanation for these findings can be found in the different alliance-technology interaction dynamics across the two groups. H7 is supported.

5 Relevance of the study and implications of the findings

This research is one of only a handful studies which have blended panel data on alliances in ten nations from two discrete datasets, SDC Corporation for alliance data and CHI for patent citations, over an 11-year period, in seeking a more complete explanation for alliance formation propensity. With two datasets, this paper can integrate two research streams, the technology commonality or learning explanation (e.g., Stuart, 1998), as well as the prior ties or relational explanation (e.g., Gulati, 1995), to examine their relative and interaction effects on alliance formation. Using a network perspective, the paper distinguishes between direct and indirect (i.e., via third parties in the network) effects. Furthermore, with data from several nations, this enables us to ask whether location of the partners, in different countries, increases or decreases alliance formation likelihood and influences the alliance-technology interaction at a network level. The statistics show strong results for the technology variables. Direct prior alliance ties also had its hypothesised effect on alliance formation, but marginally and only for the first order (linear) term.

We can conclude that firms in the global pharmaceutical industry tend to seek partners,

- that are related in technological foundations in terms of patent citations
- that are previously directly connected by prior ties
- prefer partners from their *own* nation (*ceteris paribus*).

Firms ally with ‘known’ partners, in inter-organisational and technological terms, to create value (Gulati, 1995; Stuart, 1998). Prospective partners already familiar with each other’s work through direct patent citations or sharing common technology sources are more likely to ally with each other, in a manifestation of a local technological search (Stuart and Podolny, 1996).

However, the results also demonstrated a diminishing returns effect for the direct technology commonality variable. This suggests that partner selection is a matter of finding the optimum middle position between the extremes of technological similarities and differences between the prospective allies. Firms seek partners that have a relatively similar technological base (which facilitates inter-partner learning and coordination), but the partner should also be sufficiently distinct or differentiated (so that there is something new to learn from them).

Learning is ‘experiential’ and often involves local search behaviour towards technologically proximate partners (Duysters and Lemmens, 2003). This may be practical, but it may not be optimal, since learning requires exploration of the unfamiliar – ‘stretching’ away from current status (Lavie and Rosenkopf, 2006) into the diverse information and knowledge which new alliances can offer (Rosenkopf and Almeida, 2003). In short, the results suggest that it is best for a firm to seek a balance or optimal middle ground between very technologically similar partners on the one hand,

and prospective allies whose technological foundations are very distinct, on the other. Furthermore, our result for the interaction term indicates that there may exist a balancing mechanism of interaction on the act of alliance formation. If technical interdependencies decrease as a result of prior direct and indirect alliance ties, firms seeking critical complementary resources from the prospective partner tend to become less reliant on existing and past partners (Baum et al., 2010).

We were also interested in asking whether and how location of the partners, in different countries, contributes to the dynamics of alliances and technology learning. This is another cut at answering a general question in international business studies, as to how cross-border effects moderate other relationships. We argued that foreign knowledge, located in foreign companies, with different capabilities, regulatory and institutional environments, and target diseases, would provide a greater learning opportunity and commercial value than knowledge available from prospective partners in the same country. On the other hand, foreign partnerships – as opposed to domestic allies – also entail greater transactions costs, risk, constraints and caveats which act as deterrents to alliance formation. We proposed two opposite hypotheses. The results show – at least for this sector and time period, that all in all, international alliances are slightly less likely to occur than same-country or domestic alliances, other things being equal. The cross-border variable had a consistently negative sign. Whether this is because of propinquity (because of geographic localisation of knowledge suggested in Rosenkopf and Nerkar, 2001) or because of cross-cultural factors (Yeniyurt et al., 2009), or differences in work routines, innovation systems, and social fabric, cannot be easily distinguished in our study.

The interaction effect on the group of international pairs in our study was also negative. This is an intriguing result that deserves further study. Can it be explained by the hypothesis that in a cross-border context, there is accelerated inter-organisational learning and resultant technological convergence? Or is the negative interaction term better explained by the earlier onset of the negative aspects (costs and risks) of alliances in an international setting? This suggests the need for further fine-grained research.

Some limitations must also be acknowledged. Our data are limited to prior alliance ties and patent citations. However, the alliance literature makes clear that there are other drivers and incentives for alliance formation that this study does not cover – such as informal industry contacts between personnel such as scientists and upper managers. From a sociological perspective, individual managers and engineers are embedded in social and informal networks (Brown and Duguid, 2001). Personnel are mobile across companies, and meet at industry conferences and associations. This human capital or social network perspective could enhance a similar future study.

While our study focused on the pharmaceutical sector, further research of this type could fruitfully be done on other sectors. Since the incidence and propensity of alliances varies significantly across industries (Hagedoorn, 1993) our results may not easily replicate in industries where patents have a lower significance as indicators of knowledge creation and acquisition – or in industries where alliances, in general, are less important in strategy. In some sectors it is possible that alliances may evolve in a ‘divergent’ way (i.e., partner firms’ capabilities may become more dissimilar over the course of alliances) and, in such a case, our presumed link between alliances and convergence would not hold.

Depending on the motives and forms, participation in alliances may produce either convergence through learning or divergence through skill substitution (Nakamura et al., 1996). Mowery et al. (1996) find that alliances sometimes lead partner firms to become technologically more convergent, and sometimes more divergent, depending on the alliance types and motives. Cantwell and Barrera (1998) hypothesised that alliances in the chemical industry are generally associated with coordinated learning, and exhibit technological convergence. By contrast, in the electrical equipment industry, each partner asserts its own sphere of influence with increasing divergence of firms' technological focus. As a general rule, firms in the global chemical-pharmaceutical industry approach alliances as vehicles for learning. Powell et al. argue that "when the knowledge base of an industry is both complex and expanding and the sources of expertise are widely dispersed, the locus of innovation will be found in networks of learning, rather than in individual firms" (1996, p.116). In this industry, we argue, that the fundamental rationale for alliances is learning rather than skill substitution. Our results offer strong evidence for the effect of the technology commonality variable on a firm's propensity to form learning alliances. Due to data constraints, however, our study could not examine specific knowledge characteristics (Zhang and Baden-Fuller, 2010) or technological circumstances (Baum et al., 2010) where either technological commonality or prior ties could be more important in a firm's decision to form an alliance with a particular partner.

6 Summary and conclusions

Who allies with which partner, and why? Much of the alliance literature has used firm level studies, without taking into account the identities of partners, or without reference to the overall network relationships in the industry. Studies based on network data are considerably fewer (e.g., Gulati, 1995; Stuart, 1998; Ahuja, 2000), perhaps because of the difficulties of assembling data, especially when two distinct datasets are sought to be combined, as in this study. This study builds upon and combines Gulati's (1995) work on alliance networks and Stuart's (1998) on technology networks, and examines the interaction of the two, with a cross-border context as an underlying variable. Panel data on alliances and patent citations over an 11-year period supports our hypothesis that alliance and technology networks co-evolve in interaction and, thereby, affect the dynamics of subsequent alliance formation.

In particular, this study's results suggest that, despite changes in the pharmaceutical industry that call for a larger geographical scope over which to amortise escalating R&D budgets, ceteris paribus, when prospective allies belong to different nations, this slightly reduces the propensity for alliance formation over the propensity to form a domestic alliance. Apparently, the perceived negative effects of international alliances outweigh the positive aspects of cross-border alliances such as novel technology and access to the foreign partner's institutional and cultural knowledge. The interaction term results also tentatively suggest – for further research – the possibility that the net value of foreign alliances erodes at a faster rate than the rate at which domestic alliances lose value because technological convergence occurs faster and/or the negative aspects of foreign partnerships set in earlier.

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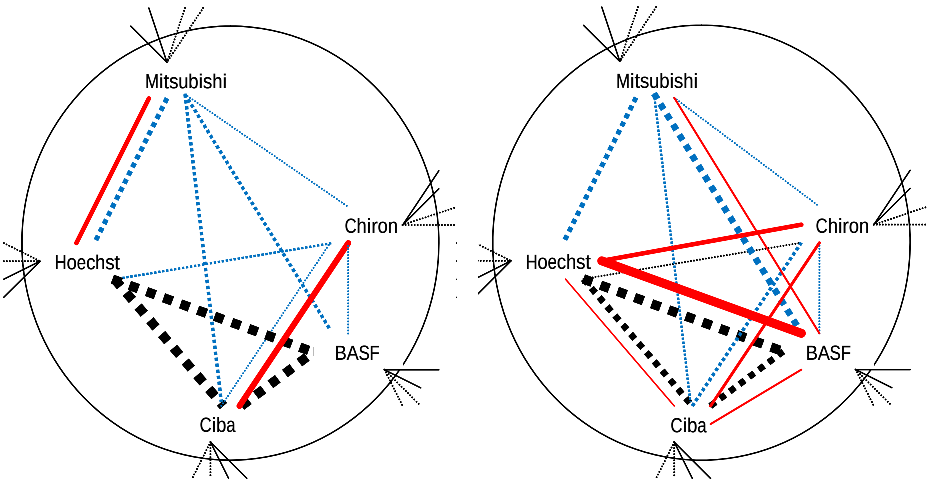
Appendix

Only five companies are depicted below – only as an illustration – since otherwise the maps would become too crowded and undecipherable. Lines going outside the circles represent links with other firms in the industry network which are not shown.

Figure 2 Illustration of network mapping, (a) period 1: first six years (b) period 2: second six years (see online version for colours)



One can map an industry network in several ways, for example by tracing the network of existing inter-organisational or alliance ties between each pair of firms. The blue *dotted lines* represent patent cross-citations between a pair of companies and the width is proportional to the intensity of their patent cross-citation ratios. *Solid lines* in red indicate the presence of at least one alliance. The thickness of solid line is proportional to our index of the strength of their inter-organisational ties between the two companies. Tracing technology commonality yields a very different industry map. The figures above combine technological (dotted line) and inter-organisational (solid line) linkages and one can see in the above that

1 the dotted and solid lines linking the firms are quite different

2 they change over time.

For instance, in period 1, the thick dotted lines (significant technological commonality) between Hoechst and BASF suggested an increased likelihood that they would form an alliance. This indeed is shown to have taken place (solid line) in period 2. As seen above, alliance ties and technology commonalities evolve over time.