MARKET NETWORKS AND THE VALUE IN KNOWLEDGE EXCHANGES: EVIDENCE FROM BIOTECHNOLOGY STRATEGIC ALLIANCES

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by

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Abstract
Researchers have argued that market networks are an integral part of the firm's value output, but the extent to which the structural characteristics of firms and their partners in market networks mediate the link between network embeddedness and value generation remains a largely unexplored area of research. This paper investigates whether diffusion mechanisms within market networks enable the latter to selectively impute the value of inter-organisational knowledge exchanges. It empirically determines the extent of this phenomenon in the context of the strategic alliance market network in the biotechnology industry. I find evidence that the structural positions of biotechnology firms and their partners in the network of strategic alliances are significant predictors of wealth gains from the announcement of knowledge exchange deals. The market reacts more to announcements of tacit knowledge exchange deals by firms on the periphery of the strategic alliance market network. Moreover, the more central a firm's partner in the network the higher the wealth gains from the announcements.

JEL Codes: D83; D84; L14

Keywords: Alliances, social networks, value, knowledge, centrality

1. Introduction

Network theory research studies the effects of the structure of inter-organisational networks and the position of firms within them on economic behaviour (Granovetter 1985), strategic actions (Gulati 1999a; 199b; Gulati *et al* 2000) and competitive behaviour (Gnyawali and Madhavan 2001). Firms' ties with organisations that have direct relevance to their core economic interests and value creation (e.g. strategic alliances) form market networks. A strategic alliance market network at any given point in time is the set of connections established by past alliances in the industry, where firms are the nodes in the network and prior alliances represent the ties linking these nodes.

Research on the effects of the embeddedness of firms in market networks has focused extensively on firm performance differentials. For instance, Baum and Oliver (1991) and Mitchell and Singh (1996) showed that alliances raised organisational survival rates. Powell *et al* (1996) found that companies that had formed many alliances experienced accelerated growth rates. Although the evidence rests heavily on the side that alliances engender superior performance, the extent to which the structural characteristics of the focal firm and its partners in market networks mediate the link between network embeddedness and value generation remains a largely unexplored area of research. Anand and Khanna (2000) suggested that firms with greater experience with alliances may have enhanced capabilities in generating value from such relationships. Kogut (2000) argued that the capabilities of firms embedded in market networks are dependent on the principles by which cooperation among firms is coordinated and supported by the network. Thus, market networks are an integral part of the firm's value output, i.e. output is a function of resource inputs, such as capital and labour, as well as value accrued from membership in market networks. Researchers are now beginning to address the issue of *how* membership in market networks forms part of the value of knowledge-intensive businesses (Karamanos 2002; Choi and Karamanos 2002).

I argue that market networks are organic components of the value created through inter-organisational knowledge exchanges, and that networks are in a position to affect the imputation of value of knowledge exchanges for *selected* firms. Diffusion mechanisms within networks enable the latter to selectively impute and know the value of inter-organisational knowledge exchanges. The purpose of this paper is to address the following research questions:

1. What are the diffusion mechanisms within market networks that drive the selective imputation of value of inter-organisational knowledge exchanges?

2. How do the characteristics of a firm's structural embeddedness in market networks affect the selective imputation value of inter-organisational knowledge exchanges?

3. What is the extent to which networks selectively affect the diffusion of knowing the value of inter-firm knowledge exchanges, and how can it be empirically measured?

The empirical locale for this paper is the high-technology industry of biotechnology and I study the effects of the strategic alliance market network on the creation of value. From literature on diffusion we distinguish two strands of theories that are necessary to modelling how the diffusion of knowing exchange value through market networks works, namely diffusion of learning and diffusion of fads. Sections 2 and 3 develop the theoretical framework of how each of these mechanisms affects the imputation of value of inter-organisational knowledge exchanges. In sections 4, 5 and 6, I describe the empirical analysis for testing the hypotheses, results are presented and conclusions drawn.

2. Imputation of exchange value as a learning process

In this section I examine how market networks act as institutions that facilitate the diffusion of knowing exchange value as a learning process. Scott (1995) emphasised that "institutions are multifaceted systems incorporating symbolic systems – cognitive constructions and normative rules – and regulative processes carried out through and shaping social behavior". In developing the learning component of the model, the normative and cognitive aspects of networks as institutions are considered.

Normative aspect of the learning process: A strand of social network theory research has shown that networks of clients, collaborators, suppliers, as well as social relations through working together and being educated together enhance common experiences and help partners gain greater awareness of each other's fundamental value systems and norms (Noreen 1988, Huber 1991). Shared values and norms nurture the expectation that parties will proactively and voluntarily provide timely and rich information necessary for a successful relationship (Heide and John 1992; Inkpen and Birkenshaw 1994). For example, norms such as willingness to value and respond to diversity, openness to criticism and tolerance of failure have been shown to contribute to knowledge creation (Leonard-Barton 1995).

Another strand of social network theory research studies how ties to networks affect a firm's trustworthiness (Coleman 1990). Trust is defined as anticipated cooperation (Burt and Knez 1995, p257) and incorporates the notion of partner credibility, which facilitates the transfer of knowledge. For instance, Szulanski (2000) found that credibility was negatively correlated to the difficulty of initiating transfers of best practice within organisations. Trust also becomes the principal mechanism through which the productive potential of collaborative resources is realised (North and Thomas 1975). This is so because it stimulates the perception of new combinations (Moran and Ghoshal 1999) and co-ordinates collaboration (Dabholkar *et al* 1994). Trust increases the learning scope of knowledge exchanges because it encourages open communication and rapid information exchange (Powell 1990), which subsequently promote the development of exchange norms. In turn, norms facilitate the creation and exchange of resources "that are crucial for high performance but are difficult to value and transfer via market ties" (Uzzi 1996, p678). In summary, knowledge exchanges can be better co-ordinated and valued through trust, and trusted firms have normative proximity with the networks they are embedded in, which increases the learning potential between organisations and the network.

The cognitive aspect of the learning bandwagon: At the individual level "cognition is almost always collaborative" (Levine *et al* 1993, p599), meaning that "when a group of individuals is brought together, each with their own knowledge structure about a particular information environment, some kind of emergent collective knowledge structure is likely to exist." (Walsh 1995, p291). At the inter-organisational level, the emergent collective knowledge structure or cognitive proximity has been dubbed strategic frame (Huff 1982), industry recipe (Spender 1989, p69), taxonomic mental model (Porac and Thomas 1990), or macro-culture (Abrahamson and Fombrun 1994, p730).

The institutionalisation of cognitive frameworks in the sense of shared mind-sets provides the necessary context for rich knowledge exchanges (Boisot 1995). Frequent social and professional interactions, dependence on supplier networks and recruitment from a common network of professionals lead to a high level of information exchange and shared mind-sets (Reger and Huff 1993). In the same vein, Krackhardt and Stern (1988) argued that a firm's network of friendship ties enhances co-operation because the face-to-face interaction that underlies these forms of information exchange is superior for interpreting social cues, capturing psycho-emotional reactions and resolving ambiguous issues. Similarly in the context of multi-unit organisations, it has been suggested that cognitive proximity implies that organisational units have prior tacit understanding that allows the effective utilisation of new knowledge (Cohen and Levinthal 1990). Moreover it has been argued that knowledge from previously unrelated actors "will be difficult to acquire and may, in fact, have limited value because of a lack of common language for understanding the knowledge" (Inkpen 1998, p76). Hence, following Friedkin (1984) who argued that ties between actors in a network constitute conduits through which beliefs are shared, we can posit that a focal firm's embeddedness in networks increases its cognitive proximity to the latter, and provides a common language, both of which facilitate knowledge exchanges and knowing value.

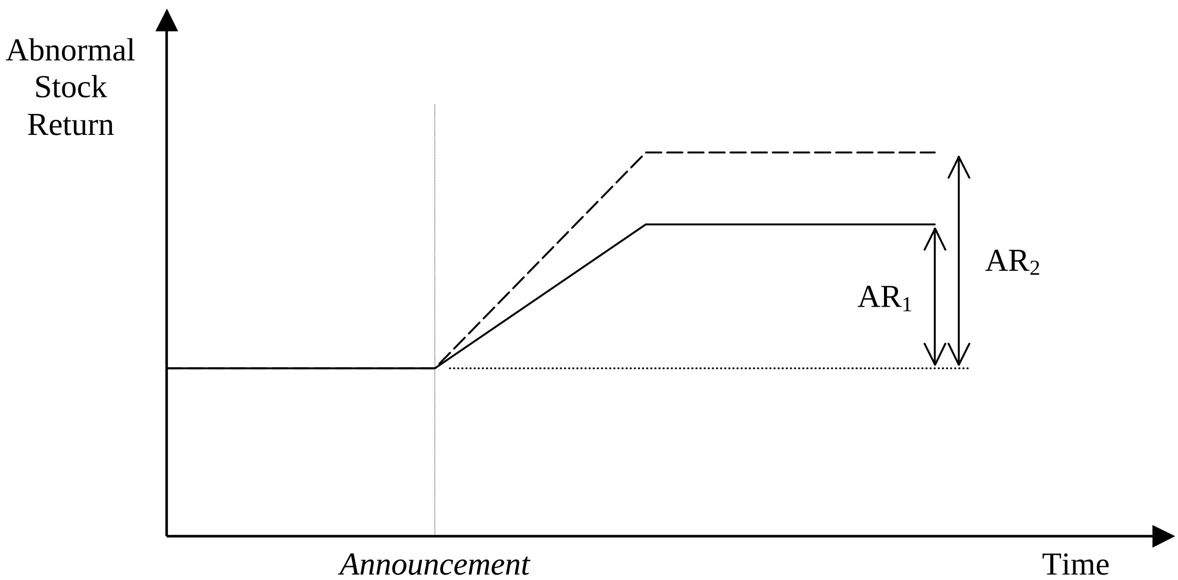
In summary, co-ordination for successful knowledge exchanges materialises through normative and cognitive proximity between partners, both of which are shaped by the embeddedness of partners in market networks. The more embedded is a firm in networks the greater the learning potential between the firm and the network, and the closer the networks are to knowing the focal firm's knowledge capital, which facilitates the imputation of its value. Thus,

> *Proposition 1a: For all knowledge exchanges, the imputation of value as a learning process increases with the focal firm's embeddedness in market networks.*

In order to develop a hypothesis out of the above proposition we need to define the notion of inter-organisational knowledge exchange value. Studies of inter-organisational collaborations (Chan *et al* 1997; Park and Kim 1997) have defined the value of knowledge exchanges as the assessment of their effectiveness, which is determined "by *ex ante* valuations of the[ir] long-term potential … as reflected in the stock market" (Park and Kim 1997, p85). The latter is a valid method because the general consensus in the literature is that (a) investors have an incentive to gather information regarding a firm's activities and (b) the firm's stock price reflects the market judgement of the likely payoffs from those activities – even though these may be occurring in the long-term (Allen 1993). Fama (1991) has shown that market reaction to a firm's announcements is semi-strong informationally efficient, but not fundamentally efficient – the latter meaning that prices are based on rational assessments of expected discounted present value. Thus, the *direction* of the market reaction is an unbiased indicator of the future impact of a particular knowledge exchange deal to the firm's future performance. Indeed, studies have repeatedly shown that the direction of immediate market reaction to collaboration deals is consistently positive (Chan *et al* 1997; Park and Kim 1997; Koh and Venkalraman 1991).

The fact that the stock market is semi-strong, informationally efficient means that the *extent* of the market reaction to a particular knowledge exchange deal cannot be considered as an absolutely rational assessment of their contribution to future firm performance. This, together with the fact that the direction of market reaction to knowledge exchange deals is consistently positive, leads to the conclusion that there is an element of a speculative bubble effect on the market reaction to a firm's announcements of knowledge exchange agreements. Thus, if increasing embeddedness in market networks enhances knowing exchange value, we expect the positive market reaction to be less for a highly embedded firm, because knowledge regarding the value of the exchange has already been incorporated into the firm's stock price before the announcement. If AR_1 and AR_2 are the wealth gains form knowledge exchange deal announcements for heavily embedded and lightly embedded firms respectively, then we expect $AR_1 < AR_2$ (see Figure 1).

Figure 1. *Market Reaction to Knowledge Exchange Announcements as a Function of the Firm's Embeddedness in Market Networks*



Embeddedness in networks has been traditionally linked in the literature with the notion of centrality (Bonacich 1987), where a central network actor is defined as having extensive ties with other actors in a network, which, in turn, are each linked to many other actors. We can thus develop Proposition 1a into Hypothesis 1a as follows:

> *Hypothesis 1a: For all knowledge exchanges, the higher the focal firm's centrality in market networks the less the positive market reaction to its knowledge exchange agreements.*

Moreover, knowledge has been classified in terms of its explicitness and tacitness (Polanyi 1966). Explicit knowledge has low imputation costs because it is searchable, identifiable, accessible, transferable, reproducible and storable (Cowan and Foray 1997). The efficiency of explicit knowledge exchanges is not expected to develop with time and their value is clear to the exchange partners. However, knowledge can remain tacit, which is more difficult to formalise, impart or exchange because it resides in peoples' beliefs, values, organisational routines and institutions (Inkpen 1998). In this case the efficiency of knowledge exchanges depends on the level of co-ordination between the exchange partners, and, as argued earlier, co-ordination itself is dependent on the firm's embeddedness in market networks. Consequently, tacit knowledge exchanges become inefficient compared to the benchmark market exchange and fundamental exchange value assessment problems arise (Chi 1994). Hence,

> *Proposition 1b: For exchanges of explicit knowledge the imputation of value as a learning process effect is small compared to that for exchanges of tacit knowledge.*

And,

> *Hypothesis 1b: The inverse relationship between a firm's centrality in market networks and the positive market reaction to its knowledge exchange agreements is weaker for explicit knowledge exchanges than for tacit knowledge exchanges.*

3. Imputation of exchange value as a fad process

Due to the inherent uncertainty of complex environments, social behaviour and economic outcomes are driven less by choices and more by constitutive rules that cannot be reduced to a mere utility maximisation function (Vanberg 1994). In the same vein, categorisation theory maintains that in complex social environments perception can be based on a set of categories that are readily available and provide cognitive efficiency (Ashforth and Humphrey 1997). Social categories work because they invoke and activate a cognitive schema about category members that the observer believes is reliable and that it conveys valid information (Fiske *et al* 1987). Previous research has shown that social categorisation mechanisms give rise to a variety of constructs, such as organisational image (Dutton *et al* 1994), organisational reputation (Fombrun and Shanley 1990), and rankings through status hierarchies (D'Aveni 1996).

We start our analysis by suggesting that the imputation of value can be driven by the focal firm's external image or reputation as conveyed by the market networks it is embedded into. Image and reputation emanate from the perceptual dimension of networks and they are defined as "an observer's impression of the actor's disposition to behave in a certain manner" (Clark and Montgomery 1998, p65). They suffer from the principal caveat that it is possible they are driven by the firm's desire to present themselves as socially acceptable, and they are unreliable because they are susceptible to manipulation by impression management strategies (Fombrun and Shanley 1990).

Abandoning organisational reputation and image as a means of knowing exchange value, we consider status as a signal of the underlying quality of an actor's products in relation to the perceived quality of that actor's competitors' products (Fombrun and Shanley 1990; Podolny 1993). Podolny stressed that status becomes more reliable when "the loose linkage between status and quality is mediated by a producer's ties to others in the market" (Podolny 1993, p832). The linkage between status and value is strengthened by the focal firm's structure of embeddedness in networks, and, in this case, the construct of status can determine expectations of future conduct (Berger *et al* 1980).

It is important however to clarify which dimension of the market networks drives the linkage between status and value. Sometimes status is treated as emanating from the perceptual dimension of networks. For instance, status has been operationalised as the evaluation of "the admiration for the quality of [an academic] faculty", or as academics' "impressions about the quality of faculty at each school", or "the national business community's impressions", or "reputations among top executives" (D'Aveni 1996, p186). In these cases it is assumed that status rests upon some notion of perceived value "as judged by those capable of evaluating the product" (Perrow 1961, p336 cited in D'Aveni (1996)). But what about the situation where there are no knowledgeable informants because it is impossible to objectively evaluate a product *ex ante* or when knowledgeable informants do not reach a consensus in their valuation? To overcome this limitation we propose that the imputation of value is based on a positional construction of the focal firm's status. This is a ranking system based on positional rather than reputational network data – which are data "from among the occupants of particular, formally defined positions or group memberships" (Scott J., p58). The efficacy of such a ranking system stems from a firm's inability to manipulate its position in network because the latter is derived solely from the firm's network ties, i.e. activities, events and relations in which it is actually involved. Thus, *Proposition 2: For all knowledge exchanges, the imputation of exchange value as a fad process operates via a positional ranking mechanism reflecting the focal firm's structure of embeddedness in networks of true relationships with partners.*

A network assigns the focal firm to a social category according the structure of the focal firm's embeddedness. Network parameters are the means of deciphering and quantifying the structure of the focal firm's embeddedness in the network and, subsequently, the means of assigning it to a social category. Social categories are bound together by the principle of homophily, i.e. the cohesive effect of similarity. Homophily refers to a perception of oneness with others, belonging to a social category (Ashforth and Mael 1989, p21), as well as the tendency for social actors to interact with similar others (Blau 1977). Thus,

Proposition 3: Market networks assign firms to social categories according to network parameters defined by the firms' structure of embeddedness in these network. Members of the same social category are bound together by homophily.

For instance, biotechnology firms are typically embedded in the network of life science research scientists, and they are assigned to social categories according to their structure of embeddedness in this network. For example, a focal firm may be assigned to the social category of ′biotechnology-firms-with-ties-to-star-scientists′ – scientists who make "numerous commercially valuable discoveries" (Liebeskind *et al* 1996, p430). Most of these stars work in universities and research institutions, and they are not willing to abandon their university appointments and laboratory teams for the sake of commercial biotechnology (Zucker *et al* 1998). Focal firms that are members of the ′biotechnology-firms-with-ties-to-star-scientists′ social category are bound together by homophily, defined by the network parameter ′ties to star scientists in the life science research network′.

Social categories to which firms are assigned are not equally salient. For instance, in the biotechnology industry, the ′biotechnology-firms-with-ties-to-star-scientists′ social category is much more salient than the ′biotechnology-firms-with-no-ties-to-star-scientists′ category, and it is the salience of star scientists amongst the life science research network that assigns high salience to the ′biotechnology-firms-with-ties-to-star-scientists′ category. Thus, if a firm is linked with highly salient network partners then it is assigned to a highly salient social category by that network.

Following Knoke and Burt's (1983) definition of prominent network actors, a firm's network partners are salient within a network to the extent that they are visible to other actors in the network because of their extensive ties within the network. For instance, in the biotechnology community, salient venture capital firms will be those most frequently involved in the supply of venture capital to biotechnology firms. Thus, salience in networks is measured as a centrality concept that captures the extent of ties of a focal actor to the rest of the network (Bonacich 1987). In summary, a salient social category in a network is defined by central network actors and the focal firm is assigned to it if it is linked to these actors.

When a focal firm has ties to a central actor, the latter plays the role of a third-party referent for subsequent exchanges the focal firm will have with the network, because the focal firm finds itself increasingly indirectly connected to the network through the central actor's other ties. For example, Timmons and Bygrave (1986) found that for new ventures the amount of finance venture capitalists provide, and the price at which they provide it, is important. However, "who the venture capitalists are" is as important because venture capitalists' specialised know-how includes their "web of contacts and networks" (162). In which case Burt and Knez (1995) argued that the indirect connections would make the focal firm more salient because they would convey information relating to the focal firm. This flow of information would make the network more certain of their imputation of the focal firm value. Depending on the frame through which the network sees the focal firm – positive or negative – it will be seen as trustworthy or not (Burt and Knez 1995, p261) and, accordingly, the imputation of exchange value produced by the indirect ties of the focal firm through a salient network partner will be positive or negative.

Moreover, ties with central network actors will not only increase the flow of information through indirect ties to the network, but the network partner's salience in itself increases the credibility of the stories conveyed by the indirect ties. This is so because central network actors are considered powerful in that their perception of the network matches the ′actual′ network – they know the network – and actors who have knowledge of networks are considered trustworthy (Granovetter 1992) and more influential (Krackhardt 1990). Trusted network actors are also credible because credibility is largely determined by trustworthiness (Perloff 1993). Cental network actors generate credible information about the focal firm, as, for instance, in the case of a well-regarded pharmaceutical firm performing due diligence before entering into a collaboration agreement with a biotechnology start-up firm. Because of the increased credibility of the information conveyed by the indirect ties through central network actors there is status transfer from the central actor to the focal firm, which is capable of starting fads regarding the focal firm's value. Depending on the frame through which the network sees the focal firm – positive or negative – the focal firm's ties with central network actors will have a positive or negative effect on knowing exchange value. In summary, central network actors hold power in that they act as social referents who affect the imputation of exchange value within market networks. Thus,

> *Proposition 4: Firms are assigned to social categories of high value salience if they are linked to central market network partners. The higher the salience of a focal firm's social category the stronger the network effects on the imputation of value of its exchanges.*

It was argued earlier that the short-term market reaction to knowledge exchange agreements is positive and that this positive reaction is partially a speculative bubble. Hence Proposition 4 becomes Hypothesis 2, as follows:

> *Hypothesis 2: For all knowledge exchange, depending on the frame through which a market network sees a firm, the higher the centrality of the firm's exchange partners the stronger the positive or negative network effects on the market reaction to its knowledge exchange agreements.*

4. Data and methods

4.1 Dependent variable and regression model

The hypotheses developed in the previous two sections were tested in the context of the strategic alliance network of UK dedicated biotechnology firms (DBFs). We used regression analysis to measure the impact of the structural positions of DBFs in the strategic alliance network on the value of their stock when a new alliance is announced. The dependent variable was the impact of an alliance announcement (event) on day *t* on the value of firm *i*, measured by the abnormal stock market return (AR_{it}) surrounding the event. *Ex post* performance of an alliance will not be perfectly predicted by this *ex ante* estimate. Instead, abnormal returns reflect the expected value that the market believes the firm will capture by entering into a particular alliance.

ARs were calculated from raw return (R_{it}) data. R_{it} is calculated from the observed share price and dividend behaviour of the DBFs examined. The raw return for firm *i* on day *t* is defined as:

$$R_{it} = \frac{P_{it} + D_{it} - P_{i(t-1)}}{P_{i(t-1)}}$$

where P_{it} is the stock price for firm *i* on day *t* and D_{it} is the dividend (if any). We used daily data on the stock price of each DBF to calculate R_{it} for a 300-day estimation period prior an event as well as for the event day(s). Abnormal stock returns were based on the Market Adjusted Model residual, with the FTSE All Share Index used as benchmark. This is a suitable index as it is not overly dependent on stock price movements in the biotechnology sector of the London Stock Exchange. Hence, abnormal stock return for each event was calculated as the difference between the firm's raw return (R_{it}) and the market return that day (R_{mt}):

$$AR_{it} = R_{it} - R_{mt}$$

I identified a pool of over 400 alliances of different types announced by UK biopharmaceuticals and diagnostics DBFs from 1992 to 1999. Data were collected from Wire News databases, company announcements, the Recombinant Capital database (www.recap.com), and DBFs websites. From the initial pool, I excluded (a) deals announced before the corresponding DBFs began listing their stock, (b) deals for which the exact date of announcement is not verifiable or known precisely, and (c) extensions of existing deals because it was assumed that the market had incorporated that information at the time of the original announcement. After these exclusions 209 alliances were retained which were formed in period 1994-2000. Abnormal returns for these knowledge exchange deal announcements formed the sample data points for the regressions.

Alliances activity in the UK biotechnology sector intensified in 1997-2000, with the largest number of agreements in one year being 54 in 1998 (Table 1). I identified four alliances types, which involve different types of knowledge exchanges between partners, as shown in Table 1: (a) Research or Development (some including licensing options), (b) Licensing or Technology Transfer, (c) Marketing and/or Distribution (some include licensing), and (d) Combined Development, Licensing and Marketing/Distribution. Of the 209 data points, 54% of the announcements involved research or development agreements, 20% licensing or technology transfer agreements, 9.5% marketing or distribution agreements and 16% complicated agreements that combined development, licensing and marketing. We can see that research or development alliances are dominant over marketing because most relations start as research or development agreements with licensing and marketing options should the projects come to fruition, and also because, up to recently UK biopharmaceutical DBFs have only managed to bring a very small number of final products to the market.

Table 1. *Distribution of Strategic Alliances by Year and Type*

Alliance Type	1991	1992	1993	1994	1995	1996
Research or Development	1	1	0	5	4	9
Licensing or Technology Transfer	0	0	0	4	5	5
Marketing or Distribution	0	0	0	0	0	5
Development, Licensing and Marketing	0	1	0	1	3	6
Yearly Total	1	2	0	10	12	25
Cumulative Total	1	3	3	13	25	50
Yearly Total as Percent of Cumulative Total	0.48	0.96	0.96	4.8	5.7	12.0

	1997	1998	1999	9/2000	Total
Research or Development	21	32	25	15	113
Licensing or Technology Transfer	7	11	3	7	42
Marketing or Distribution	1	7	5	2	20
Development, Licensing and Marketing	8	4	6	5	34
Total	37	54	40	29	209
Cumulative Yearly Total	87	141	180	209	-
Yearly Total as Percent of Cumulative Total	17.7	25.8	19.1	13.9	100%

Although Research or Development deals may include some commercialisation clauses, neither licenses nor commercialisation are the main focus of such agreements. Combined Development, Licensing and Marketing/Distribution agreements materialise at a much later stage of product development than Research or Technology agreements and include detailed licensing and commercialisation clauses. Thus, the nature of knowledge exchanges in combined Development, Licensing and Marketing/Distribution agreements, and Research or Development agreements, is different. In the former it is more explicit technological know-how that is exchanged and developed with a clear objective of immediate commercialisation, whereas in the latter knowledge is more tacit as the technology is still in a very early stage of development.

We used a cross-sectional regression model to test the hypotheses. The model is described by the following equation:

$$CAR_i = \beta_0 + \sum \beta_{mi} x_{mi} + \varepsilon_i$$

where x_{mi} is the m_{th} predictor variable for the data point *i* and ε_i is the error term vector. The predictor variables included independent (centrality) variables and control variables.

4.2 Independent variables - Mapping the UK biotechnology alliances market network

Alliances in the biotechnology industry have been very popular, with over 7,000 alliances formed by US biotechnology companies in 1976-2001, and 1,142 alliances by European biotechnology companies in 1995-2001 (Ernst & Young 2001). The popularity of alliances in the biotechnology industry means that there exist dense market networks in the US and Europe.

Market network data for this study came from strategic alliances and joint ventures by UK public DBFs in the biopharmaceuticals and diagnostics sectors between 1986 and 1999. The UK public biotechnology industry is the dominant force in Europe and accounts for 41% of the European industry in terms of number of firms (Ernst & Young 2001). The biopharmaceuticals and diagnostics sectors dominate the UK biotechnology industry and account for 88% of the industry in terms of assets and 58% in terms of number of companies (Arthur Andersen 1997).

The number of reported alliances from 1983 to 1999 increased every year and totals to 575 (Figure 2), with R&D, Licensing, Marketing and Distribution deals being the most prolific (Table 2). Data were collected from Wire News databases, company announcements, the Recombinant Capital database (www.recap.com), and DBFs' websites. Each type of alliance requires varying levels of organisational commitment and leads to differing levels of organisational interdependence and knowledge transfer. To reflect these differences alliances were weighted according to the intensity of the relationship between the partners, as shown in Table 2 and in accordance with previous alliance research (Nohria and Garcia-Pont 1991). As shown in Table 3, alliances partners included (a) diversified firms (pharmaceuticals, chemicals), (b) other DBFs, (c) suppliers, and (d) research institutes, with the majority of partners being diversified firms (55%) and other DBFs (34%). In terms of the geographical distribution of the partners we found that the majority of alliances (44%) were with US firms (Figure 3).

Figure 2. *Number of Alliances by UK Public DBFs 1983-1999*

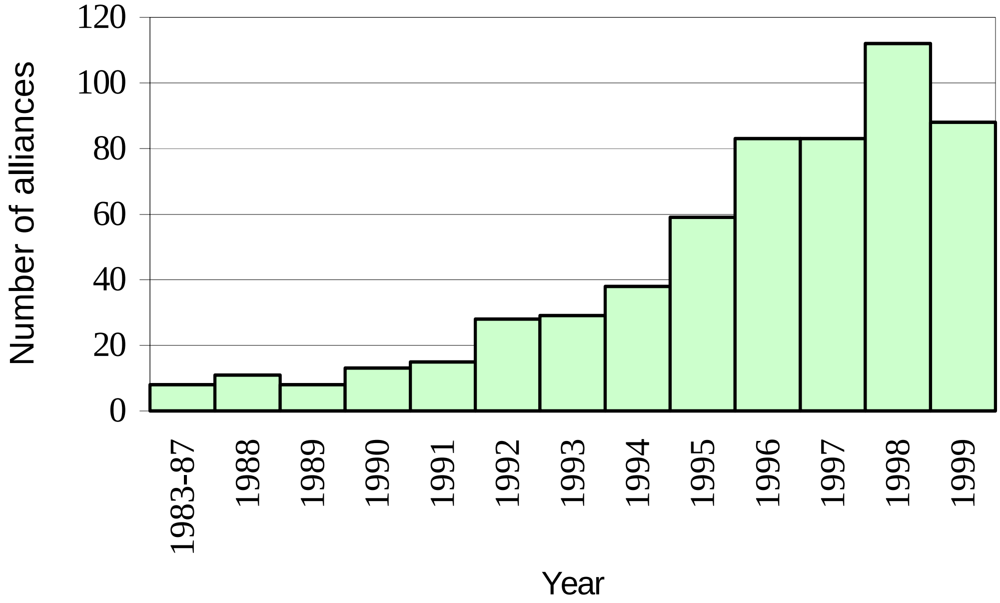


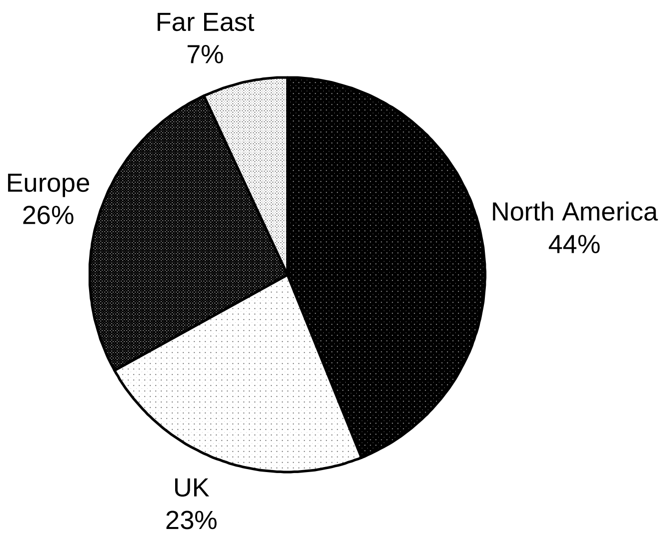
Table 2. *Alliance Types, Frequencies and Weights*

Agreement Type	Frequency	Weight
Joint Venture	18	9
Alliances Involving Equity	52	8
R&D	322	7
Marketing	37	6
Distribution	31	5
Licensing	80	4
Supply/Manufacture	19	3
Asset or Technology purchase	14	2
Option	2	1
TOTAL	575	

Table 3. *Distribution of Alliances by Partner Type*

Partner Type	Number of deals	
Diversified firms		
Pharmaceutical	293	
Chemical	15	
Food	7	
		315 (55%)
Other DBFs		
Therapeutics	12	
Diagnostics	23	
Services and Suppliers	37	
Agricultural or Veterinary	6	
		195 (34%)
Suppliers		28 (5%)
Research Institutes		37 (6%)

Figure 3. *Geographical Distribution of UK Public DBFs' Alliance Partners*



Hypotheses 1a and 1b assessed the effect of the focal firm's (DBF) centrality in the strategic alliance market network on the abnormal returns from its knowledge-intensive collaborations. Alliance data were organised in DBF-by-partner data matrices for each year in the period 1992-1999 and a DBF-by-DBF adjacency matrix was calculated for each year of observation, using UCINET V software. The DBF-by-DBF matrix for each year was used to calculate the DBF centrality for each year in the period 1992-1999. For each knowledge exchange deal in the sample I used the DBF centrality for the previous year as the independent variable for testing Hypotheses 1. Therefore, focal firm centrality refers to the centrality of the DBF in the network the calendar year before the deal announcement was made, which captures the knowing exchange value as learning process in a window of minimum one year and maximum two years depending on whether the deal was announced at the beginning or the end of the calendar year. This is an appropriate time window given that the average age for strategic alliances to start creating value is about two years. All centrality scores were normalised relative to the maximum possible in the network for each year.

Centrality can be measured in several ways, each of which is associated with different interpretation (Freeman 1979; Faust 1997)[1]. When measuring prominence, salience or involvement in a network, DEGREE_C centrality is used, which is defined as the number of ties an actor has in the network, normalised by the maximum number of ties that an actor can have in that network. I also used CLIQUE_C centrality, which I defined as the number of cliques in the network that an actor belongs to. A clique is a sub-set of a network in which the actors are more closely and intensely tied to one another than they are to other members of the network. In this analysis, a clique was defined as three or more actors who have all possible ties present among themselves. We expect that different knowledge circulate in each clique since the former cannot circulate from one clique to another as freely as between clique members.

Hypothesis 2 assessed the effect of the focal firm's partners' centrality in the

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[1] Betweenness centrality is not appropriate for this analysis because it measures an actor's power in the network rather that prominence or salience. Also, in theory, closeness centrality could have been tested but, technically, it cannot be computed for fragmented networks such as those in my sample, as there are infinite distances between actors. Closeness centrality defines an actor's ability to access independently all other members of the network and reflects freedom from the control of others. Freeman (1979: 225) associated closeness centrality with efficient communication, stating that closeness "means fewer message transmissions, shorter lines and lower costs". In contrast, actors in the periphery of networks will encounter inadequate quality and quantity of information.

alliances network on the abnormal returns to the focal firm's knowledge-intensive collaborations. A different approach was taken for calculating the centrality of the alliance partner because the hypothesised effect is reputational and therefore the time window needs to extend much more than two years. A partner-by-partner adjacency matrix was used to calculate partner centralities for each year of observation, but the matrix for each year accumulated all the alliance activity amongst industry participants until each particular year. This, I made the reasonable assumption that the fad effect is cumulative over time. Two alternative measures of partner centrality were tested, namely PARTNER DEGREE_C and PARTNER CLIQUE_C centrality. In order to allow for network effects to show an impact all centrality measures were lagged by one year relatively to the dependent variable. When DBFs partners' centrality scores were calculated we found that we had scores for 87 events to test hypotheses 2. This is so because the partner centrality measures were lagged behind the dependent variable by one year and for many events there was no previous involvement of the particular partner in the network.

4.3 Control variables

A number of variables known or expected to affect the dependent variable were included as controls. First, I controlled for the size of DBFs, which is typically treated as an exogenous variable that is indicative of the extent to which a firm has economies of scale and scope, as well as its relative endowment with resources (Nohria and Garcia-Pont 1991). Findings on the effects of size on firm behaviour have been highly ambiguous, so much so that Kimberly (1976) made the argument that in many instances firm size may be capturing the residual effects of factors that were omitted from the statistical models used. Chan *et al* (1997) and Das *et al* (1998) examined the effects of firm size on abnormal returns for strategic alliances and found that it is inversely related to abnormal returns. This is so because small firms are typically involved in the upstream activities of the value chain, such as research and development, and knowledge transfer to larger firms. Doz (1988) argued that the transfer of technology is competitive in that the small firms attempt to minimise the exposure of their know-how and exercise bargaining power when collaborating with large firms. Thus, it was found that market reaction to smaller firms' collaborations is greater than the reaction to larger firms' collaborations.

Moreover, I was concerned with the effect firm size may have on the relationship between a focal firm's centrality measure and abnormal returns. Benjamin and Podolny (1999) found a negative relation between firm size and a network measure called status. Although status is not the same measure as centrality it is nevertheless a network variable related to the idea of centrality in a network of relations. Size has been used before as a control variable to reflect a firm's resource base, it can be critical to its decision to collaborate (Gulati 1995), and, ultimately, it may be related to a firm's centrality in the industry-wide network of collaborative agreements. I controlled for firm size using firms' total assets or the logarithm of total assets lagged by one year relative to the dependent variable, and I found similar results for the two measures for firm size. Here I report models that use the logarithm of total assets as a measure for control variable SIZE.

I was also concerned with the effect a DBF's alliance experience could have on abnormal returns. Anand and Khanna (2000) suggested that firms with greater experience with alliances may have enhanced capabilities in generating value from such relationships. It was also reasonable to assume that alliance experience could be highly correlated to centrality, which could introduce multicollinearity. However DBF centrality and alliance experience are calculated over different time frames so we expect such effects to be weak. I therefore introduced the control variable ALLIANCE EXPERIENCE that counts the total cumulative number of a DBF's collaborative deals up to each year of the analysis. This variable was lagged by one year relative to the dependent variable.

Another control variable in the analysis assessed whether a collaborative agreement was international in its membership. Previous studies have suggested that domestic ventures are more likely to succeed because (a) there is better information available about the partners, and (b) the reputational consequence of opportunistic behaviour is bigger in a domestic context (Gulati 1995). Also Parkhe (1993) has shown that national culture affects managerial behaviour and moderates the relation between structural variables and performance of collaborations. The cultural similarity among domestic partners enhances mutual understanding, allowing easier co-ordination and better conflict resolution among the partners. I introduced the dummy variable SAME NATIONALITY that takes the value of 1 when an alliance comprises of domestic partners, and 0 when it includes international collaboration.

Moreover, I expect different market reactions to different types of alliance, i.e. (a) R&D, (b) Licensing or Technology Transfer, (c) Marketing and/or Distribution, and (d) Combined Development, Licensing and Marketing/Distribution. This is so because each type of alliance entails varying levels of organisational commitment, leads to differing levels of organisational interdependence and risk. I used the control variable AGREEMENT TYPE to control for these differences. It takes the value of 1 for R&D, 2 for licensing, 3 for marketing and 4 for combined development, licensing and marketing deals. Also, the dummy variable HORIZONTAL was included in the analysis, which takes the value of 1 when the data point involves a horizontal collaboration (i.e. partners come from the same industry sector and thus are similar businesses) and 0 when partners are dissimilar business. Prior research has shown that investors' reactions to joint ventures announcements were greater when collaboration partners were dissimilar businesses (Balakrishnan and Koza 1993).

Finally, I included a dummy variable for each year in the analysis (called TIME1 to TIME6) in order to capture effects that may arise from temporal market trends. In a limited way these dummy variables test the claim that markets can be more or less optimistic at times, thus affecting abnormal returns in a temporal fashion. They also capture the net effect of the various temporal macro-economic, sector-specific factors that may be influencing market returns in the UK biopharmaceuticals sector. The variables used in the different regressions and their predicted signs are summarised in Table 4.

Table 4. *Regression Variables and Predicted Signs of Relationships*

Independent variables	***Definition***	***Predicted sign***
DEGREE_C	The number of ties a DBF has in the network each year of the analysis	-
CLIQUE_C	The number of cliques in the network that a DBF belongs to each year of the analysis	-
PARTNER DEGREE_C	The cumulative number of ties a partner has in the network over the years of the analysis	+
PARTNER CLIQUE_C	The cumulative number of cliques a partner belongs to over the years of the analysis	+

Control variables	***Definition***	***Predicted sign***
TIME1 to TIME6	Calendar time	No prediction
SAME NATIONALITY	1 if both partners are domestic; 0 otherwise	+
HORIZONTAL	1 if partners are similar; 0 otherwise	-
ALLIANCE EXPERIENCE	Number of previous alliances entered by the DBF until the year before the year of the announcement	+
SIZE	Log of last known DBF total assets before event date	-
AGREEMENT TYPE	1 if R&D; 2 if License; 3 if Marketing; 4 if Commercialisation	+

5. Abnormal returns and regression analysis results

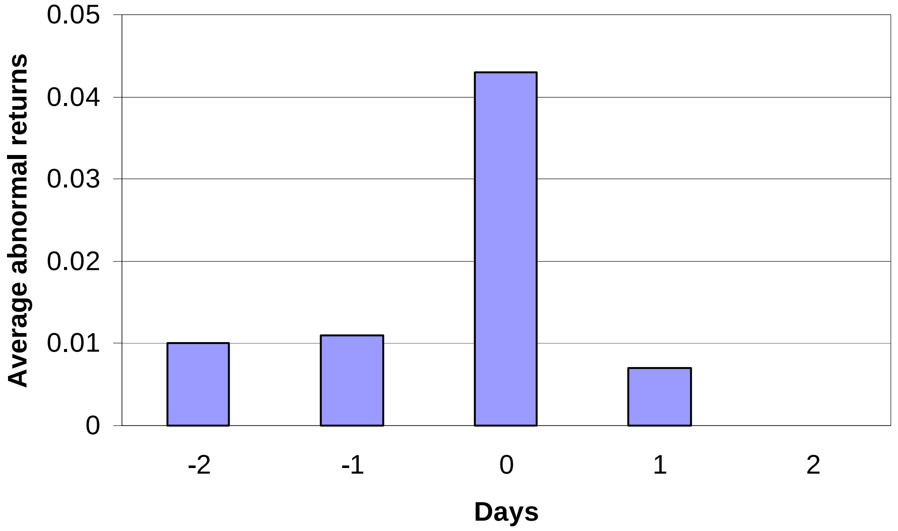
First I calculated the abnormal returns (ARs) for the 209 alliances announcements in the sample. Excluding contemporaneous announcement of alliances, which can render results unreliable, I found that the average AR for the day of the announcement was 4.3% and 6.1% for days "-1 to +1"; both these results are statistically significant (see Table 5). These results confirm earlier results by Das *et al* (1998), Chan *et al* (1997) and Koh and Venkataraman (1991). I also found that cumulative abnormal returns (CARs) for Research or Development events, Licensing or Technology Transfer events and Development, Licensing and Marketing events together (collectively described in Table 5 as Technological) were positive and statistically significant. On the other hand, CARs for Marketing or Distribution events (collectively described in Table 5 as Marketing) were positive for event windows "0" and "-1 to +1", and became negative when event window widened, but in all cases they were statistically indistinguishable from zero. Research or Development CARs were close to CAR values for all events, Licensing or Technology Transfer CARs were higher than CARs for all events, and Development, Licensing, and Marketing CARs were on average double the CAR values for all events. This result provides support to the argument that abnormal returns are higher for events that involve products at a later stage of development than pure research or products in early development. In other words, the higher uncertainty associated with tacit knowledge exchange deals curtails market reaction compared to more explicit knowledge exchange deals.

Table 5. *Cumulative Abnormal Returns for Different Event Windows*

	All Alliances	**Technological**	**Marketing**	**t-statistic**[2]
No. of data points =	***174***	***129***	***13***	
AR Day "0"	0.043 (14.42)*	0.037 (10.50)*	0.018 (1.66)$^{++}$	1.31 [0.200]
CAR Days "-1 to +1"	0.061 (11.96)*	0.057 (9.34)*	0.009 (0.45)	2.14 [0.042]$^{+}$
CAR Days "-2 to +2"	0.071 (10.80)*	0.072 (9.15)*	-0.012 (-0.48)	3.04 [0.005]$^{+}$

Notes:
(1) Numbers in parentheses in column cells represent associated t-statistics assuming cross-sectional dependence for a test of the null hypothesis that the cross-sectional mean is zero.
(2) The reported t-statistic is test value for a difference-of-means t-test. The number in square brackets represents the associated probability value, [P(T≤t) two-tail test].
$^{*}p < 0.001$, $^{**}p < 0.01$, $^{+}p < 0.05$, $^{++}p < 0.1$

Figure 4. *The Average Impact Over Time of an Alliance Announcement on DBF Share Value*



As shown in Figure 4, the average impact of an alliance announcement dies out one day after the announcement day, and there is some AR due to information leakage the day before the announcement. In order to test the robustness of the regressions results, I decided to separately test the AR on the day of the announcement (AR_0), the AR the day before the announcement (AR_-1), and the AR the day following the announcement (AR_+1), as the regression dependent variable. This way I can see whether centrality has a different effect at different days surrounding the announcement.

Table 6 presents the descriptive statistics and correlations for the variables in the regression models for testing hypotheses 1. DEGREE_C and CLIQUE_C centralities are highly correlated between themselves because they describe similar quantities. This poses no problem because they are examined separately in the statistical analysis. ALLIANCE EXPERIENCE and SIZE are slightly correlated with DEGREE_C and CLIQUE_C centralities, which suggests there may be some multicollinearity across these variables. If they prove to be significant in the regression analysis we will have to examine whether their effects on the dependent variable are independent or whether they interfere, and if so we will have to determine in which way they do. I use the VIF statistic to determine the possible existence of multicollinearity. VIF values of less than 2 indicate low multicollinerity in which case results can be trusted.

Table 6. *Descriptive Statistics and Correlation Matrix of Regression Variables*

	N	Mean	S.E. of Mean	Minimum	Maximum
AR_0	209	0.036	0.007	-0.238	0.733
AR_-1	209	0.032	0.006	-0.180	0.560
AR_+1	209	0.029	0.006	-0.230	0.490
Degree_C	209	4.130	0.348	0	21.875
Clique_C	209	0.398	0.052	0	4
Same Nationality	209	0.294	0.032	0	1
Horizontal	209	0.289	0.032	0	1
Alliance Experience	209	15.955	0.731	1	49
Size	209	3.199	0.089	-0.503	5.362
Agreement Type	209	1.891	0.080	1	4
Time1	209	0.050	0.015	0	1
Time2	209	0.055	0.016	0	1
Time3	209	0.119	0.023	0	1
Time4	209	0.184	0.027	0	1
Time5	209	0.254	0.031	0	1
Time6	209	0.194	0.028	0	1

	AR_0	AR_-1	AR_+1	Degree_C	Clique_C	Same Nationality	Horizontal	Alliance Experience	Size	Agreement Type	Time1	Time2	Time3	Time4	Time5	Time6
AR_0	1															
AR_-1	0.812	1														
AR_+1	0.806	0.771	1													
Degree_C	-0.152	-0.206	-0.139	1												
Clique_C	-0.132	-0.156	-0.100	0.838	1											
Same Nationality	0.002	-0.010	0.011	0.006	0.052	1										
Horizontal	-0.006	-0.011	-0.046	0.102	0.073	-0.145	1									
Alliance Experience	-0.060	-0.080	-0.043	0.350	0.262	-0.018	0.089	1								
Size	-0.100	-0.146	-0.109	0.242	0.143	-0.071	0.174	0.472	1							
Agreement Type	0.128	0.061	0.066	0.063	0.076	-0.044	-0.123	0.111	0.172	1						
Time1	-0.070	-0.085	-0.082	-0.021	-0.123	0.003	-0.045	-0.085	-0.016	-0.039	1					
Time2	0.136	0.056	0.110	0.044	-0.070	0.085	-0.057	0.016	0.099	0.081	-0.055	1				
Time3	-0.112	-0.064	-0.047	-0.127	-0.157	-0.002	-0.031	-0.182	0.014	0.158	-0.084	-0.089	1			
Time4	0.013	0.004	0.008	-0.047	-0.047	0.004	-0.048	-0.195	-0.119	0.001	-0.109	-0.114	-0.175	1		
Time5	0.021	-0.044	0.003	-0.135	-0.097	-0.100	0.007	-0.014	-0.030	-0.105	-0.133	-0.140	-0.215	-0.277	1	
Time6	0.052	0.068	0.061	0.182	0.195	0.043	0.048	0.201	0.134	-0.041	-0.112	-0.118	-0.181	-0.233	-0.286	1

All regression models include the control variables AGREEMENT TYPE, SIZE, ALLIANCE EXPRERIENCE, HORIZONTAL, SAME NATIONALITY, and TIME1 to TIME6. Positive coefficients of variables indicate a direct relationship with abnormal returns with respect to that variable; negative coefficients show a inverse relationship with abnormal returns with respect to that variable.

Hypothesis 1a was tested using the sample of 209 events with a variety of models to account for the different dependent variables and DBF centrality measures, as shown in Table 7. Models I to III test the principal dependent variable AR_0, models IV to VI the dependent variable AR_-1 and models VII to IX the dependent variable AR_+1. Models I, IV and VII are base models to assess effects other than those attributed to the position of the biotechnology firm in the alliance network.

Models II and III confirm hypothesis 1a, i.e. that there is a significant inverse relationship between degree and cliques centralities and the abnormal return the day of the announcement. The less embedded the DBF has been in the network of strategic alliances in a period of up to two years before a new collaboration is announced, the higher the abnormal returns of the DBF's shares the day of the announcement. Models V and VI also confirm hypothesis 1a because they show that there are significant network effects on the wealth gains due to information leakages one day before the announcement. In this case, degree and clique centralities are more significant (and with higher coefficients) than on the day of the announcement indicating that the speculation due to information leakages is less for higly embedded firms, or that there is less information leakages associated with highly embedded firms. On the other hand, models VII and IX show that network effects on wealth gains cease to be significant one day after the announcement, indicating that there are factors other than network embeddedness that affect wealth gains the day after the announcement.

AGREEMENT TYPE is also a significant predictor of wealth gains: commercialisation agreements entail higher potential returns than research and development agreements, which indicates that the markets factor in the higher probability of commercialisation success associated with later stage research involving more explicit and easily transferable knowledge. This finding verifies Pisano (1989) who observed that in the biotechnology industry the degree of uncertainty for transaction-specific know-how is greater in collaborations that encompass basic R&D than in collaborations that involve the transfer, utilisation, or commercialisation of existing know-how. This result also confirms the similar result from the abnormal return analysis at the beginning of section 5.

We can see from Table 7 that, with very few exceptions, time is not significant, indicating that there is no broad temporal trend in the abnormal returns, i.e. market reaction has been consistent through time and that there have not been significant macro-economic UK biotechnology-specific industry factors affecting abnormal returns.

Table 7. *Regression Models Testing Hypothesis 1a*

Model	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**
Dependent variable	**AR_0**			**AR_-1**			**AR_+1**		
Intercept	0.038 (0.188)	0.042 (0.138)	0.045 (0.116)	0.075 (0.003)*	0.080 (0.001)*	0.083 (0.001)*	0.035 (0.134)	0.038 (0.102)	0.039 (0.096)
Agreement Type	0.015 (0.018)*	0.016 (0.014)*	0.016 (0.011)*	0.008 (0.172)	0.008 (0.136)	0.009 (0.107)	0.006 (0.227)	0.006 (0.202)	0.007 (0.184)
Size	-0.010 (0.112)	-0.009 (0.159)	-0.010 (0.140)	-0.010 (0.076)	-0.087 (0.122)	-0.009 (0.101)	-0.009 (0.089)	-0.008 (0.123)	-0.008 (0.106)
Alliance Experience	-0.001 (0.483)	-0.0002 (0.849)	-0.0004 (0.639)	-0.0007 (0.347)	-0.0002 (0.789)	-0.0004 (0.517)	-0.00001 (0.951)	0.0002 (0.711)	0.0000 (0.920)
Horizontal	0.009 (0.561)	0.012 (0.465)	0.010 (0.504)	0.004 (0.806)	0.006 (0.659)	0.005 (0.723)	-0.001 (0.911)	0.0001 (0.991)	-0.0004 (0.955)
Same Nationality	-0.001 (0.931)	-0.001 (0.951)	0.0008 (0.958)	-0.005 (0.697)	-0.005 (0.716)	-0.003 (0.830)	-0.001 (0.918)	-0.001 (0.935)	-0.0000 (0.994)
Time1	-0.020 (0.579)	-0.022 (0.538)	-0.035 (0.341)	-0.047 (0.145)	-0.049 (0.119)	-0.060 (0.049)*	-0.016 (0.598)	-0.017 (0.564)	-0.024 (0.427)
Time2	0.066 (0.065)	0.066 (0.064)	0.053 (0.143)	0.010 (0.740)	-0.010 (0.742)	-0.005 (0.882)	0.051 (0.082)	0.050 (0.081)	0.043 (0.143)
Time3	-0.031 (0.291)	-0.037 (0.199)	-0.044 (0.131)	-0.035 (0.166)	-0.042 (0.089)	-0.050 (0.048)*	-0.0001 (0.974)	-0.005 (0.824)	-0.009 (0.723)
Time4	0.006 (0.802)	0.005 (0.857)	-0.002 (0.952)	-0.021 (0.360)	-0.026 (0.302)	-0.029 (0.186)	0.010 (0.614)	0.009 (0.657)	0.006 (0.774)
Time5	0.015 (0.533)	0.009 (0.714)	0.005 (0.833)	-0.020 (0.334)	-0.026 (0.185)	-0.031 (0.137)	0.013 (0.483)	0.009 (0.633)	0.008 (0.681)
Time6	0.027 (0.274)	0.028 (0.242)	0.024 (0.312)	0.005 (0.801)	0.007 (0.731)	0.003 (0.891)	0.026 (0.187)	0.027 (0.166)	0.025 (0.207)
DEGREE_C	-	-0.003 (0.023)*	-	-	-0.004 (0.003)*	-	-	-0.002 (0.052)	-
CLIQUE _C	-	-	-0.022 (0.032)*	-	-	-0.024 (0.006)*	-	-	-0.012 (0.141)
Adjusted R^2	0.028	0.049	0.046	0.007	0.049	0.041	0.005	0.10	0.002
Number of data	209	209	209	209	209	209	209	209	209
"Size" VIF statistic	1.43	1.44	1.44	1.43	1.44	1.44	1.43	1.44	1.44
"Alliance Experience" VIF statistic	1.53	1.61	1.55	1.53	1.61	1.55	1.53	1.61	1.55
"Centrality" VIF statistic	-	1.20	1.19	-	1.20	1.19	-	1.20	1.19

Note: Significance level in parentheses
*p<0.05

SIZE and ALLIANCE EXPERIENCE are consistently not significant predictors of abnormal returns, and there seems to be no multicollinearity problems with these variables because VIF numbers are around 1.5. SAME NATIONALITY, indicating alliance partners of the same nationality, is also not significant, indicating that the market does not perceive alliances with international partners as riskier due to cultural differences than domestic alliances. HORIZONTAL, indicating similarity between partners' business scope, is not significant. This indicates that, unlike the result for joint ventures (Balakrishnan and Koza 1993), markets do not believe that strategic alliances are more successful when they involve dissimilar businesses.

Splitting the data into two groups of explicit and tacit knowledge exchange deals respectively and running regression models for each group separately tested hypothesis 1b. Pure R&D collaborations (AGREEMENT TYPE = 1) were characterised as tacit. Licensing, marketing, or commercialisation deals (AGREEMENT TYPE = 2,3,4) were assigned to the explicit category. DEGREE_C and CLIQUE_C focal firm centrality were tested and the results are shown in Table 8. For tacit knowledge exchanges, DEGREE and CLIQUE centralities are significant and for explicit knowledge exchanges, centralities are insignificant, indicating no network effects. On average, VIF coefficients were about 1.75, which is within acceptable limits. These results support hypothesis 1b that network effects on knowing exchange value are stronger in the case of tacit knowledge deals.

Hypothesis 2 was tested using the sample of 87 events for which it was possible to calculate centrality scores for DBFs' partners. Abnormal returns for the day of the announcement (AR_0) and cumulative abnormal returns for one day before and one day after the announcement (CAR_-1+1) were used as alternative dependent variables. Table 9 presents the descriptive statistics and correlations for the variables in the regression models. PARTNER DEGREE_C and PARTNER CLIQUE_C centralities are highly correlated between themselves because they describe similar quantities. This poses no problem because they are examined separately in the statistical analysis. PARTNER DEGREE_C and PARTNER CLIQUE_C are slightly correlated with AGREEMENT TYPE and HORIZONTAL, which is expected because different partner types are associated with different agreement types. ALLIANCE EXPERIENCE and SIZE are also slightly correlated which suggests there may be some multicollinearity. I use the VIF statistic to determine the possible existence of multicollinearity. VIF values of less than 2 indicate low multicollinerity in which case results can be trusted. I used TIME as a dummy variable that takes a different value for each year of the analysis. The models for testing hypothesis 2 are shown in Table 10.

Table 8. *Regression Models Testing Hypothesis 1b*

Model	**I**	**II**	**III**	**IV**	**V**	**VI**
Agreement Type	**TACIT**			**EXPLICIT**		
Intercept	0.102 (0.006)*	0.115 (0.002)*	0.118 (0.002)*	0.024 (0.601)	0.028 (0.549)	0.031 (0.500)
Size	-0.005 (0.558)	-0.003 (0.711)	-0.004 (0.618)	-0.009 (0.489)	-0.008 (0.517)	-0.008 (0.516)
Alliance Experience	-0.002 (0.161)	-0.002 (0.230)	-0.002 (0.161)	0.0004 (0.699)	0.001 (0.353)	0.0009 (0.462)
Horizontal	0.014 (0.500)	-0.021 (0.318)	0.021 (0.317)	-0.013 (0.620)	-0.014 (0.584)	-0.018 (0.495)
Same Nationality	-0.006 (0.752)	-0.013 (0.516)	-0.008 (0.697)	-0.004 (0.878)	0.0001 (0.997)	-0.0001 (0.973)
Time1	-0.055 (0.271)	-0.054 (0.269)	-0.075 (0.139)	0.006 (0.912)	0.003 (0.957)	0.007 (0.906)
Time2	-0.031 (0.612)	-0.018 (0.759)	-0.049 (0.495)	0.127 (0.009)*	0.125 (0.010)*	0.114 (0.021)*
Time3	-0.094 (0.035)*	-0.111 (0.013)*	-0.113 (0.012)*	0.028 (0.493)	0.026 (0.515)	0.018 (0.668)
Time4	-0.041 (0.221)	-0.054 (0.102)	-0.059 (0.084)	0.055 (0.179)	0.063 (0.126)	0.054 (0.180)
Time5	-0.010 (0.747)	-0.022 (0.486)	-0.026 (0.421)	0.017 (0.646)	0.010 (0.781)	0.008 (0.822)
Time6	-0.035 (0.254)	-0.034 (0.264)	-0.038 (0.222)	0.100 (0.014)*	0.098 (0.014)*	0.093 (0.022)*
DEGREE Centrality	-	-0.004 (0.030)*	-	-	-0.004 (0.138)	-
CLIQUE Centrality	-	-	-0.026 (0.050)*	-	-	-0.022 (0.206)
Adjusted R^2	0.026	0.063	0.054	0.054	0.069	0.062
Number of data	108	108	108	101	101	101
"Size" VIF statistic	1.73	1.75	1.74	1.47	1.47	1.47
"Alliance Experience" VIF statistic	1.74	1.76	1.74	1.68	1.96	1.83
"Centrality" VIF statistic	-	1.30	1.26	-	1.33	1.32

Note: Significance level in parentheses
*p<0.05

Table 9. *Descriptive Statistics and Correlation Matrix of Regression Variables*

	N	Mean	S.E. of Mean	Maximum	Minimum
AR_0	87	0.048	0.011	0.680	-0.240
CAR_-1+1	87				
Partner Degree_C	87	0.391	0.023	1	0.020
Partner Clique _C	87	0.306	0.032	1	0
Same Nationality	87	0.320	0.050	1	0
Horizontal	87	0.150	0.038	1	0
Alliance Experience	87	17.264	1.201	49	1
Size	87	3.348	0.113	5.360	1.090
Agreement Type	87	2.060	0.130	4	1
Time	87	4.860	0.170	7	1

	AR_0	CAR_-1+1	Partner Degree_C	Partner Clique _C	Same Nationality	Horizontal	Alliance Experience	Size	Agreement Type	Time
AR_0	1									
CAR_-1+1	.833	1								
Partner Degree_C	.142	.165	1							
Partner Clique _C	.129	.148	.919	1						
Same Nationality	.021	.077	-.102	-.193	1					
Horizontal	.001	.012	-.324	-.250	-.151	1				
Alliance Experience	-.079	-.046	.043	-.011	-.076	.126	1			
Size	-.179	-.157	-.037	-.092	-.121	.149	.453	1		
Agreement Type	.222	.201	-.234	-.302	-.012	.085	.184	.194	1	
Time	-.099	-.113	-.163	-.120	.014	.247	.154	-.010	-.068	1

The results show that PARTNER DEGREE_C and PARTNER CLIQUE_C centralities are significant and both have a positive effect on abnormal returns of alliance announcements, which verify hypothesis 2 and indicate that in uncertain contexts the prominence of a focal firm’s exchange partner becomes a base of evaluation. Consistent with the results for hypotheses 1 SIZE, ALLIANCE EXPERIENCE, HORIZONTAL, SAME NATIONALITY, and TIME were not found to be significant, but AGREEMENT TYPE is a significant predictor of wealth gains. VIF statistics are well within acceptable limits so there is no multicollinearity and the results are robust.

Table 10. *Regression Models Testing Hypothesis 2*

Models	**I**	**II**	**III**	**IV**	**V**	**VI**
Dependent variable		**AR_0**			**CAR_-1+1**	
Intercept	0.108 (0.050)	0.042 (0.492)	0.056 (0.346)	0.053 (0.059)	0.016 (0.611)	0.023 (0.442)
Agreement Type	0.022 (0.020)*	0.026 (0.005)*	0.027 (0.005)*	0.009 (0.043)*	0.012 (0.010)*	0.012 (0.008)*
Size	-0.022 (0.061)	-0.022 (0.064)	-0.021 (0.079)	-0.010 (0.081)	-0.010 (0.085)	-0.009 (0.105)
Alliance Experience	-0.0001 (0.912)	-0.0004 (0.683)	-0.0003 (0.751)	0.0001 (0.831)	-6.406E-05 (0.909)	-8.58E-06 (0.988)
Horizontal	0.011 (0.736)	0.032 (0.333)	0.027 (0.411)	0.009 (0.590)	0.021 (0.215)	0.018 (0.275)
Same Nationality	0.0005 (0.983)	0.008 (0.732)	0.012 (0.605)	0.008 (0.539)	0.012 (0.327)	0.014 (0.242)
Time	-0.006 (0.416)	-0.004 (0.580)	-0.004 (0.534)	-0.004 (0.287)	-0.003 (0.433)	-0.003 (0.390)
PARTNER DEGREE_C	-	0.111 (0.040)*	-	-	0.063 (0.022)*	-
PARTNER CLIQUE_ C	-	-	0.008 (0.048)*	-	-	0.046 (0.025)*
Adjusted R^2	0.042	0.080	0.077	0.030	0.081	0.078
Number of data	87	87	87	87	87	87
"Size" VIF statistic	1.31	1.31	1.32	1.31	1.31	1.32
"Alliance Experience" VIF statistic	1.32	1.35	1.33	1.32	1.35	1.33
"Centrality" VIF statistic	-	1.25	1.27	-	1.25	1.27

Note: Significance level in parentheses
*p<0.05

6. Discussion and conclusions

This study found strong evidence that the imputation by the markets of the value of inter-organisational knowledge exchange deals is influenced by the structural characteristics of firms and their partners in market networks. There are network resources, in the form of diffusion mechanisms within market networks, that drive the selective imputation of value of inter-organisational knowledge exchanges. I summarize the results around two sets of findings concerning: (a) the imputation of exchange value as learning, and (b) the imputation of exchange value as fad.

Evidence showed that a firm's central position in the network of strategic alliances negatively affected wealth gains from the announcement of knowledge exchange deals. More specifically, for tacit knowledge exchange deals, the market reacts more to announcements by firms in the periphery of the strategic alliance network, which suggests that the imputation of value as learning is a significant process in operation. On the other hand, the imputation of value of explicit knowledge exchange deals does not seem to be affected by the structural position of the DBF in the network of strategic alliances. These dynamics take place one day before and on the day of the deal announcement, but die out one day after the announcement.

Moreover, the position of a DBF's partner in the network of strategic alliances is also a significant predictor of wealth gains from the announcement of knowledge exchange deals. The more central a firm's partner the higher the wealth gains, which suggests that the imputation of value as fad is a significant process in operation. This result is consistent with the argument in strategic alliance literature that a firm's important constituents view the gaining of a prestigious alliance partner as an endorsement of quality (Stuart *et al* 1999) and as a signal that conveys social status and recognition (Stuart 2000). This study has offered additional evidence to confirm that alliances with prominent partners offer endorsement benefits that are immediately and easily obtained, as indicated by superior wealth gains, even when eventually they fail to achieve the strategic objectives that led to their formation.

The results of this paper also show that alliances create value, which confirms Das *et al* (1998), Chan *et al* (1997) and Koh and Venkataraman (1991). CARs for Research or Development events, Licensing or Technology Transfer events and Development, Licensing and Marketing events together were positive and statistically significant. On the other hand, CARs for Marketing or Distribution events were positive for event windows "0" and "-1 to +1", and became negative when the event window widened, but in all cases they were statistically indistinguishable from zero. Research or Development CARs were close to CAR values for all events, Licensing or Technology Transfer CARs were higher than CARs for all events, and Development, Licensing, and Marketing CARs were on average double the CAR values for all events. This result provides support to the argument that abnormal returns are higher for events that involve products at a later stage of development than pure research or products in early development.

I found no evidence to suggest that firms learn to create value as they accumulate experience in alliances, as Anand and Khanna (2000) suggested. Perhaps this is so because I focused my attention exclusively to the biotechnology industry in the UK, and my results could not be generalised for another industries and countries. However I believe this is an interesting antithesis and more light could be shed on it if one were to repeat Anand's and Khanna's analysis with both alliance experience and centrality variables included. In this case, firm experience would reflect what they term "firm learning" and centrality would be a proxy for "market learning". This additional analysis would probably clarify whether the positive effect of the number of alliances on the announcement wealth gains reflects market learning rather than firm learning.

In conclusion, I would like to suggest a few avenues for future research. A useful extension of this study could consider the implications from a firm's participation in multiple networks such as joint patents, board interlocks, bank ties, and professional association memberships. It would also be beneficial to consider the contents of those ties based upon the different kinds of information that flow through them. For example, centrality in other networks may be significant for the imputation of value of explicit knowledge exchanges only because the contents of different network ties is different as to the types of information they carry. Another avenue for research is the use of more social network analysis tools. Density and centralisation are two structural variables that can be introduced. Rowley (1997) argued that when network density increases the average salience of social categories defined by central actors decreases. Thus value salience will increase only with increasing stakeholder centrality and decreasing network density. Centralisation is related to density but also measures how cohesion (i.e. dense network areas) is organised around particular focal actors (Marsden 1990). Highly centralised networks are like hierarchies and, in the extreme, there is only one focal actor. In decentralised networks there are no focal actors because everyone is connected to everyone else. Centralisation, then, tells as how information flows through the network structure, because in hierarchical networks focal actors at the top will control the flow of information. There are, thus, implications for informational power and influence inherent in the degree of network centralisation. Also, centralisation may give a better indication of the relative informational power of the different networks a focal firm is embedded into.

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