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Inter-firm R&D Networks in Pharmaceutical Biotechnology: What Determines Firm's Centrality-based Partnering Capability?*

Yin Krogmann†, Nadine Riedel‡ and Ulrich Schwalbe§

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Abstract

This paper analyses the inter–firm R&D network formed in the pharmaceutical biotechnology industry during the 1990s from different perspectives: theoretical network formation, firm's structural positions and its collaborations at the entire network level, and the determinants for firm's centrality–based partnering capability. The results indicate that pharmaceutical biotechnology industry has experienced a significant evolutional change in size and structure during 1991–1998. By considering individual structural positions, the descriptive statistics show that in the 1990s, established pharmaceutical companies developed into dominant star players with multiple partnerships while holding central roles in the R&D network. In the network analysis that emphasized aggregate network level, the degree–based and betweenness–based network centralization were not high implying that the distribution of overall positional advantages in the pharmaceutical biotechnology industry is, to a large degree, not unequal and even though most firms in this sector are linked to the R&D network, some of them are more active than others. The current analysis also shows that firm's efficiency, firm's dependency on its complementary resources and firm's experiences at managing partnerships are important determinants for firm's centrality–based partnering capability, which has important managerial implications for understanding firm's strategic partnering behaviour.

JEL Classification: C12, C36, D85, L24, L65, O32

Keywords: Inter-firm cooperation; R&D partnerships; Network formation; Social network analysis; Instrumental variable

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1 Introduction

High technology industries with their rapidly developing innovation and knowledge base serve as an important source for the national economy. Their development demands firms to possess knowledge and skills in multiple technological fields in order to meet market conditions. In such a dynamic and competitive industrial environment, no single firm has the ability to keep pace with the growing scientific and technological progresses without external partners (Cantner and Rake, 2011). Particularly in the high–tech sector of pharmaceutical biotechnology, as widely acknowledged in the literature, the creation of a tight inter–firm network of research and development (R&D) collaboration has become an unavoidable strategy for innovative companies (see Chiaroni *et al.*, 2008; Roijakkers and Hagedoorn, 2006; Salman and Salves, 2005). As a result, the pharmaceutical biotechnology industry has witnessed a sharply increasing frequency of inter–firm partnerships between large established pharmaceutical firms and a range of biotechnology companies in recent decades (see Hagedoorn and Roijakkers, 2002; Powell *et al.*, 2005; Rothaermel, 2000). Especially during the 1990s, the inter–firm partnerships between these two high technology sectors have successfully created a track for high technology companies to achieve progress in knowledge and innovation (Roijakkers, 2003). As more and more firms from the pharmaceutical biotechnology sector realized the importance of innovation, the cooperation between high–tech firms turned out to be dense and tight, and their communication network became "a small world" to the extent that vast numbers of firms with different national origins were all connected to each other, which consequently globalized the world market in the high technology sector. Using the information from Recombinant Capital database[1] in 1995, we could draw the global connection of the pharmaceutical biotechnology industry with the network visualization software Pajek (Nooy *et al.*, 2005), in which each red orb indicates one company and the black lines with two arrows represents the cooperation between them (Figure 1). This R&D network between firms seems to be a prime illustration for the renowned "small world phenomenon" (Milgram, 1967), which refers to the "six degrees of separation" principle

[1] Recombinant Capital is a San Francisco Bay Area–based consulting firm specializing in biotechnology alliances and reputed to have built some of the largest and most detailed biotech business intelligence databases in the world. Its clients include biotechnology and pharmaceutical companies, plus several universities active in the biotechnology area.

that the network distance between any two individuals in the world is, on average, six. Obviously, a cooperation network between firms is not distinct from a social network between people. Globalization makes the world narrow and small, and the distance is no longer an obstacle for the connections. Furthermore, integrating into such a research network enables high–tech firms to optimally share the resources that they possess. As a result, they would have opportunities to access the resources available in the whole world, and exchange technological and innovative information with greater facilities.

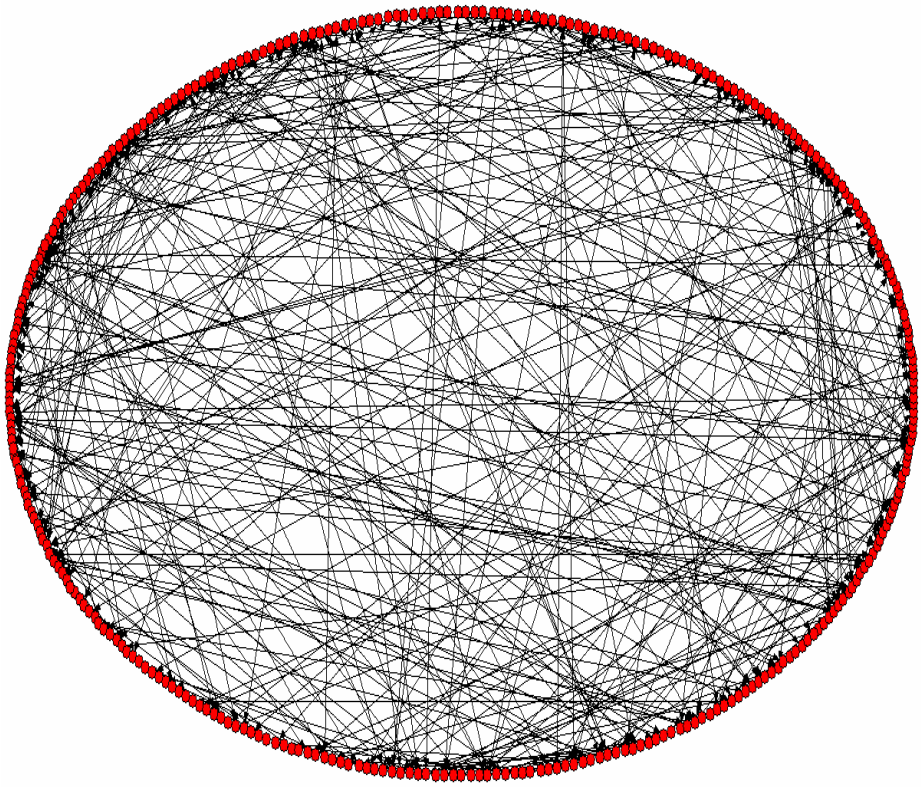

Figure 1: "Small world" of the pharmaceutical biotechnology sector in 1995; s*ource:* Recombinant Capital.

However, cooperating firms do not share equal opportunities and advantages within the same network. Goyal and Joshi (2003), from a view of theoretical network formation, indicated that collaborations used by firms to generate strategically stable networks are often asymmetric, with some firms having many collaboration links and other firms being poorly linked. This asymmetry can be observed on the core–periphery structure of the network, in which central firms that are situated in favoured structural positions have more opportunities to perform better than the firms located on the

network periphery (Hojman and Szeidl, 2004). A firm's capability to place itself centrally could be quantified by its centrality, which is one of the earliest concepts to describe an actor's strategic position in a network. There have been a number of authors who investigated the topic relating to firm's centrality on a wide range of aspects. Tsai (2001) suggested that a firm's innovative capability is significantly increased by its centrality in the intra–organizational network, which provides the opportunities for knowledge transfer and information exchange. Walter *et al.* (2007) proposed that a firm's centrality in the inter–firm network positively affects its ability to acquire knowledge from its collaboration partners. Thus, in order to obtain more chances for acquiring knowledge, a firm has to actively pursue a positional advantage by aligning itself with a central player of the inter–firm network. Santos (2003) applied longitudinal data in a sample of 225 biotech companies and found that the size of firms is positively correlated with their previous network centrality, and due to the advantages of knowledge spillovers, the development of a central position in the network positively influences firms' future growth. Powell *et al.* (1996) empirically demonstrated that a central position in inter–firm learning networks for biotechnology start–ups is related to their rapid subsequent growth. By using pharmaceutical biotechnology industry data, Hagedoorn *et al.* (2006) pointed out that firms with larger centrality–based capability are more likely to engage in future partnering activities. While the above–mentioned aspects have been rather extensively treated in the literature, relatively scarce attention has been paid to the question of what essentially determines a firm's centrality–based network capability. In the current paper, we will empirically test the possible determinative factors of a firm's centrality–based partnering capability in the pharmaceutical biotechnology industry by using the econometrics approaches of two–stage least squares (2SLS) and the optimal generalized method of moments (GMM).

The main purpose of this paper is to provide a descriptive and empirical analysis of inter–firm R&D networks in the pharmaceutical biotechnology industry. In this context, this paper exploits the insights gained from inter–firm cooperation of this high technology sector under different aspects: theoretical network formation, firm's structural positions and its collaborations at the aggregate network level, and the determinants for firm's centrality–based partnering capability in the R&D network. The remaining part of the paper is structured as follows. The second section provides the theory of network formation and its applications to firm's cooperation, especially

the cooperation between firms in the pharmaceutical biotechnology sector. It also describes the evolutional structural change in the pharmaceutical biotechnology network during the time period 1991–1998. Section 3 discusses conceptions and relevant descriptive statistics for the pharmaceutical biotechnology industry with regard to actor–level centrality and network–level centralization, and then identifies the most important players in the inter–firm R&D network of this high–tech sector during the period 1991–1998. Section 4 comprises an empirical analysis to identify the determinative factors of a firm's centrality–based partnering capability which is followed by a discussion with special attention to the managerial implications of our findings. The final section presents the major conclusions drawn from this paper.

2 The Economics of Networks

Networks play an important role as intermediary between economics and social society. The growth of modern industries and economics would be diminished to a large degree without the communication and information in a social network. Earlier studies indicated that social networks are essential for economics activities. These studies cast some lights on the networks in the labour markets in the context of networks as means of obtaining jobs (see Myers and Shultz, 1951; Rees and Shultz, 1970). This interest was further developed by the studies of Boorman (1975) and Montgomery (1991), which were crucial early bridges between the sociology literature and the economics literature (Jackson, 2007). One of the important views expressed in these studies is the choice–based perspective that underlines economic network formation, which can be captured as: individuals form or maintain relationships in their mutual interests, and avoid or remove themselves from relationships that are not beneficial. In a R&D collaboration network, firms behave analogously to individuals in the way that they form a link when the cooperation is reciprocal and delete a link that cannot bring any benefits to them. The economics behind such a network of firms is that the cooperation provides firms a way to integrate their separate resources in order to achieve the optimal efficiencies that a single firm itself cannot reach (Gottinger and Umali, 2008). This feature is especially important for the high–tech industry, in which the formation of R&D networks is regarded as an adaptive response to the rapidly growing knowledge

within the sector. In the following, some theoretical issues in the network formation will be discussed and their applications to the cooperation between firms, particularly the firms in the high–tech sector of pharmaceutical biotechnology will be addressed.

One of the fundamental concepts underlining network formation is pairwise stability, which was defined by Jackson and Wolinsky (1996). According to these authors, a network is considered as pairwise stable if no pair of players could benefit from linking, while no single player could gain by severing one of his links. This concept of pairwise stability, which involves a mutual consent to form a relationship, shows the response of players to the cost and benefits that they expect from network relationships. Issues related to group formation have also been a central concern of network theory. In the literature, group formation is modelled in terms of a coalition structure, in which coalitional membership partitions the set of players into mutually exclusive groups. Initial work on coalition formation was carried out within traditional cooperative game theory, which describes a variety of productive enterprises where the cooperation among players is beneficial (Jackson, 2007). By adopting this setting into the experiments, Myerson (1977) pointed out that cooperation leads to higher utility than separate efforts and predicted how the value should be split among members of the society, which is now referred to as the Myerson Value. Following up on this work, there have been a number of studies on cooperative games, for instance, Aumann and Myerson (1988) proposed a game of link formation in a strategic context where players anticipate the effect that communication has on cooperative opportunities and ultimately on the value that they will obtain. Apart from the studies on cooperative group formations, there have also been developments of non–cooperative theory of coalition formation, such as the open membership game of Yi and Shin (1995), the coalition unanimity game of Bloch (1995 and 1996), and the equilibrium binding agreements of Ray and Vohra (1997).

Under the aspect of network efficiency, a fundamental theoretical model which presents the value of relationship should be brought to our attention. It was proposed by Jackson and Wolinsky (1996) under the name "connection model" and has been largely adopted and developed in later studies. In the setting of this model, a link indicates social relationships which offer benefits and also involve some costs. Players benefit from both, direct relationships and indirect relationships, but benefits decrease with the distance between any pair of players to the extent that a "friend of a friend" generates a lower benefit than a friend. The results from the model imply that if the

costs of a relationship are low enough, the efficient network is a complete network (i.e., where everyone directly links to everyone). However, if the costs are very high relative to the benefits, the empty network (i.e., without any links) will be the only efficient network, and for the intermediate level of costs, the star network with the feature of pairwise stability is the efficient network structure. This "connection model" also illustrates another fundamental point of theoretical network formation, namely that there could be a tension between stability and efficiency. Specifically, in this model, a link between two players can reduce distances for all players in a network, but the player who is directly involved in this link would only consider whether or not his payoff will increase, without thinking about whether this link will increase the payoffs of others. This situation renders the pairwise stable networks inefficient. Some authors use the "connection model" to also identify the relation between efficiency and stability in a network. For instance, Bala and Goyal (2000) analyzed the "connection model" under the assumption that players form links unilaterally. In their two–way flow setting, the conflict between stability and efficiency again exists, represented by the example of telephone calls: one player makes the phone call and incurs the cost of calling, but both players benefit from the information exchange during the telephone conversation. Another example relating to the tension between efficiency and stability is the "co–author model" (see Jackson and Wolinsky, 1996). The story accompanies the collaboration on a research project: when one researcher decides to join in a project with another researcher, he dilutes the time he spends on each of his current projects, which negatively affect his productivity on each of his projects. This decline in productivity influences the researcher but also affects each of his collaboration partners. However, he would only account for the negative effect on his own utility but ignore the effects on his collaboration partners. As a result, the inefficiency of a stable network becomes evident. To resolve the conflict between efficiency and stability, the players within a network could bargain over payments by themselves to attain the efficiency, or the government could take actions of reallocating value through transfers, such as taxes and subsidies (Goyal, 2007).

As discussed above, the theoretical modelling and analysis reveal the impact of social science on economic behaviour. In particular, it raises the question of how social structure influences the economic decisions and interactions of an individual. It is necessary to make a forecast of how the individual's behaviour changes in response to network changes in a way that the individual would have a general idea of what will

occur when the network changes and adopt a corresponding behaviour to the present situation. The initial concept underlying network formation is that of costs and benefits, which not only reflects the perspective of an individual, i.e., that the individual forms relationships based on reciprocity, but also reflects the perspective of the society as a whole. It is not surprising that maximizing individual incentive may not reach the maximum of the societal welfare, which results in a tension between efficiency and stability within a network. This tension could be minimized by different channels but its intensity is difficult to be observed and measured, which may also depend on the specific feature of theoretical settings. These theoretical models not only provide the prospects about how the decisions of players contribute to the network formation, but also highlight their role in explaining phenomena of collaborations between firms. Kawamata and Tamada (2004) analyzed firm's incentive to form pairwise links and pointed out that cost–sharing is a powerful incentive as it allows firms to pool their resources and avoid wasteful duplications. Similar results were also found in earlier studies (see d'Aspremont and Jacquemin, 1988; Kamien *et al.*, 1992; Kamien and Zang, 1993; Katz, 1986; Suzumura, 1992). In these cost–reducing alliance references, as summarized by Bloch (2004), either the collaboration covers all the companies in the industry (as in Kamien *et al.*, 1992; Suzumura, 1992), or the industry can be partitioned into symmetric leagues (as in Kamien and Zang, 1993). Besides, Goyal and Moraga–González (2003) presented a survey of research on the formation of networks between firms and found that markets shape the firm's incentives to form pairwise links, while links between firms affect their competitive position and thereby shape the function of the market. Goyal and Moraga–González's (2001) analysis highlighted the relationship between market competition, firm's incentive to invest in R&D, and the architecture of collaboration networks. Their results showed that the complete network is pairwise stable and industry–profit maximizing, and firms may engage in excessive collaborative activities in a model with endogenous choice of effort. Goyal and Joshi (2003) also studied the firm's incentives to form collaboration links and found these incentives to be intimately related to the nature of market competition. Their results suggested that under quantity competition there is no conflict between efficiency and stability, whereas there is a conflict under price competition. Song and Vannetelbosch (2007) showed that the likelihood of a conflict between efficiency and stability is considerably reduced to cases of very small or quite large spillovers. They suggested that governments should be allowed to subsidize R&D whenever spillovers are not very

small. More recently, Zikos *et al.* (2010) proposed that state–owned enterprises may be used as policy instruments in tackling the potential conflict between individual and social incentives for R&D collaboration.

In the high technology industries, R&D collaborations between firms have become especially crucial, since the knowledge base and innovation process in these industries are diversified and rapidly developing. This high–tech environment requires that firms upgrade their knowledge and skills constantly to meet market conditions and customers' expectations. Particularly in the pharmaceutical biotechnology industry, firms can no longer exclusively rely on their internal skills and knowledge to maintain their innovativeness. It is also necessary for them to access external sources of knowledge through collaborations and create innovative products to harvest the knowledge (Zahra and Bogner, 2000). Under these circumstances, in order to gain competitive advantages, pharmaceutical companies and biotechnology firms established inter–firm R&D collaborative network in a variety of partnership forms. This R&D network formation in fact grounds on the choice–based perspective that is emphasised in the network theories. From this view, the cooperation between pharmaceutical companies and biotechnology firms is based on their reciprocal interests to the extent of their complementarities. By connecting to biotechnology firms, large pharmaceutical companies could successfully undergo the challenges of technological innovation during so called "biotechnology evolution" and keep their dominant position in the high–tech industry (Chiaroni *et al.*, 2008), while building up the cooperation with pharmaceutical companies provided biotechnology firms with important sources to sustain their innovative capabilities. This R&D network cooperation offers pharmaceutical biotechnology firms various opportunities to increase their efficiency of R&D efforts, reduce their cost and risk investing in the launching R&D projects, and create options for knowledge and innovation development. Thus, the R&D cooperation is a key factor in explaining the industrial growth of this high technology sector (Gottinger and Umali, 2008).

However, the inter–firm R&D cooperation may potentially create negative externalities since a partner could simply attain the knowledge and patents through free–riding, which results in an essential conflict between private incentive and social incentive that we also observed in the network theoretical models. Yet from the prospects given by a variety of studies, different authors have different opinions about whether R&D cooperation could lead to such a conflict. Anbarci *et al.* (2002) pointed

out that if the degree of complementarity in a certain industry–pair is high enough, despite the typical free–riding problem, R&D group formation can secure high technological improvement, profits and social welfare; but if complementarity is extremely low, research cooperation may lead to lower profits and social welfare. Röller *et al.* (1998) suggested that R&D cooperation in complementary industries would seem to have positive welfare implications, while Katz *et al.* (1990) proposed that the private incentives for R&D investment are diminished relative to the social incentive. Although the puzzle still exists in the effects of research cooperation, the cooperative R&D efforts are generally encouraged by governmental policies, such as permissive antitrust treatment of R&D joint ventures and by cross–licensing agreements or similar arrangements among firms (Katz, 1986). Nevertheless, a cooperative R&D network serves as a mechanism that produces the information efficiency and consequent social benefit. It plays an important role in generating technology advances and expanding the stock of technological capabilities. The importance of R&D cooperation can indeed be observed through the growth of partnering activity in the high technology sector over the years (see Hagedoorn, 1995; Gulati, 1995). In the following, we will exhibit and analyze the evolutional cooperation trend in the pharmaceutical biotechnology industry during the period 1991–1998[2]. The data source that has been used for Figure 2 and Figure 3 is the Recombinant Capital database.

[2] This time period was chosen since it covers the years in which inter–firm partnering activities in pharmaceutical biotechnology has risen rapidly (Galambos and Sturchio, 1998; Powell *et al.*, 1996; Senker and Sharp, 1997).

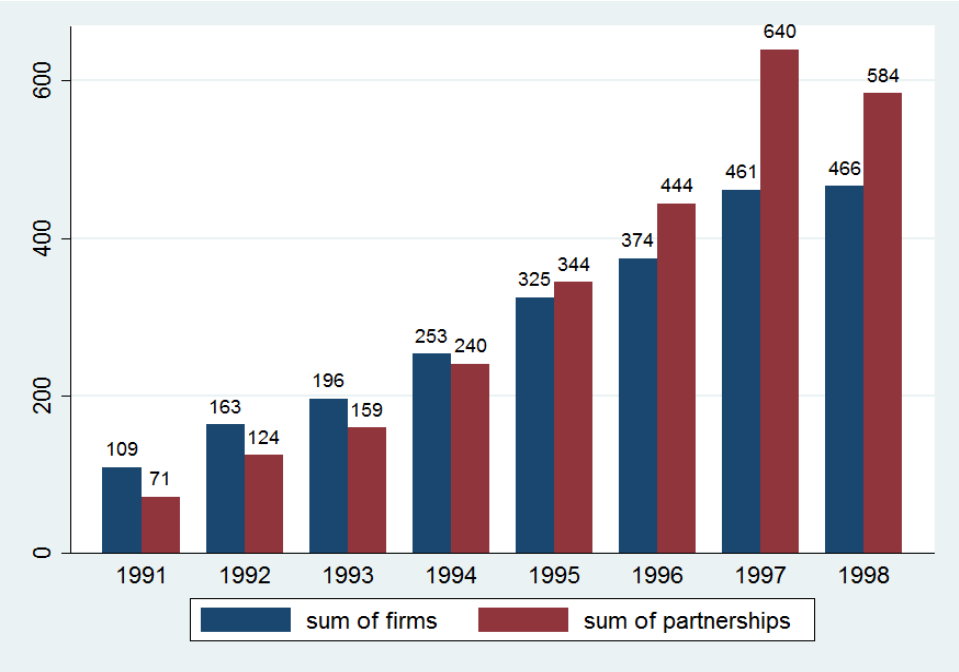

Figure 2: The growth of firms and R&D partnerships in the pharmaceutical biotechnology network, 1991–1998; *source*: Recombinant Capital.

As shown in Figure 2, the historical data on inter–firm R&D partnering in the pharmaceutical biotechnology industry reveal an overall growth pattern in the time period 1991–1998: the number of firms which participate in the R&D network dramatically increases from 109 in 1991 to 466 in 1998. As a result, the number of their partnerships increases as well, reaching a peak of 640 in 1997 and then declining to 584 in 1998. The important industrial and technological changes in this time period have led to the growing interdisciplinary nature of scientific and technological developments, increasing costs of R&D projects and higher risks surrounding R&D (Hagedoorn, 1993 and 1996), which were a major force driving pharmaceutical companies and biotechnology firms into the cooperative research network. As a result, the network size and partnering activity in this high–tech sector largely increased overall (Figure 2).

Figure 3 provides a graphical representation of the evolutional structural changes of the inter–firm R&D network in the pharmaceutical biotechnology industry during the time period 1991–1998. Red orbs represent the pharmaceutical biotechnology firm within the R&D network and solid black lines with two arrows represent partnerships between two companies. The graph shows that the network gradually developed from isolated pairs of cooperating companies with a few clusters of multi–collaborator

networks to a large complex network with numerous interrelated companies. During the early 1990s, large pharmaceutical companies established absorptive capacity for assimilating new biotechnology knowledge and built up joint R&D agreements with a variety of biotechnology firms. As a result, by 1993, nearly 196 firms were involved in this research network representing 159 partnerships (Figure 2). There were still a number of one–on–one ties and some isolated research clusters in the early 1990s (Figure 3). For the mid–1990s, Figure 3 shows a denser, more connected R&D network in which around 300 firms (Figure 2) were engaged in a multitude of joint R&D agreements. This results from common research efforts and many newly established joint R&D agreements between pharmaceutical companies and biotechnological firms during these years. Although the majority of companies were connected to most other firms through many partnerships, there were still a few isolated companies cooperating amongst themselves, not linking up to any of the other network participants. However, in the late 1990s, a very large, extremely dense R&D network had developed involving 466 companies (by 1998) that were nearly all connected to each other by numerous direct and indirect ties (Figure 2 and 3). Due to intensity of inter–firm cooperation in this high–tech sector, it would have been very unusual for a firm not to cooperate with others. Also, under the high–tech environment with dynamic and innovative knowledge base, a firm cooperating in a R&D network is less likely to retreat its participation from the cooperation (Powell *et al.*, 1996). Thus, inter–firm cooperation, particularly the intensive R&D collaboration, is likely to remain an important feature of the pharmaceutical biotechnology sector (Powell, 1998; Senker and Sharp, 1997).

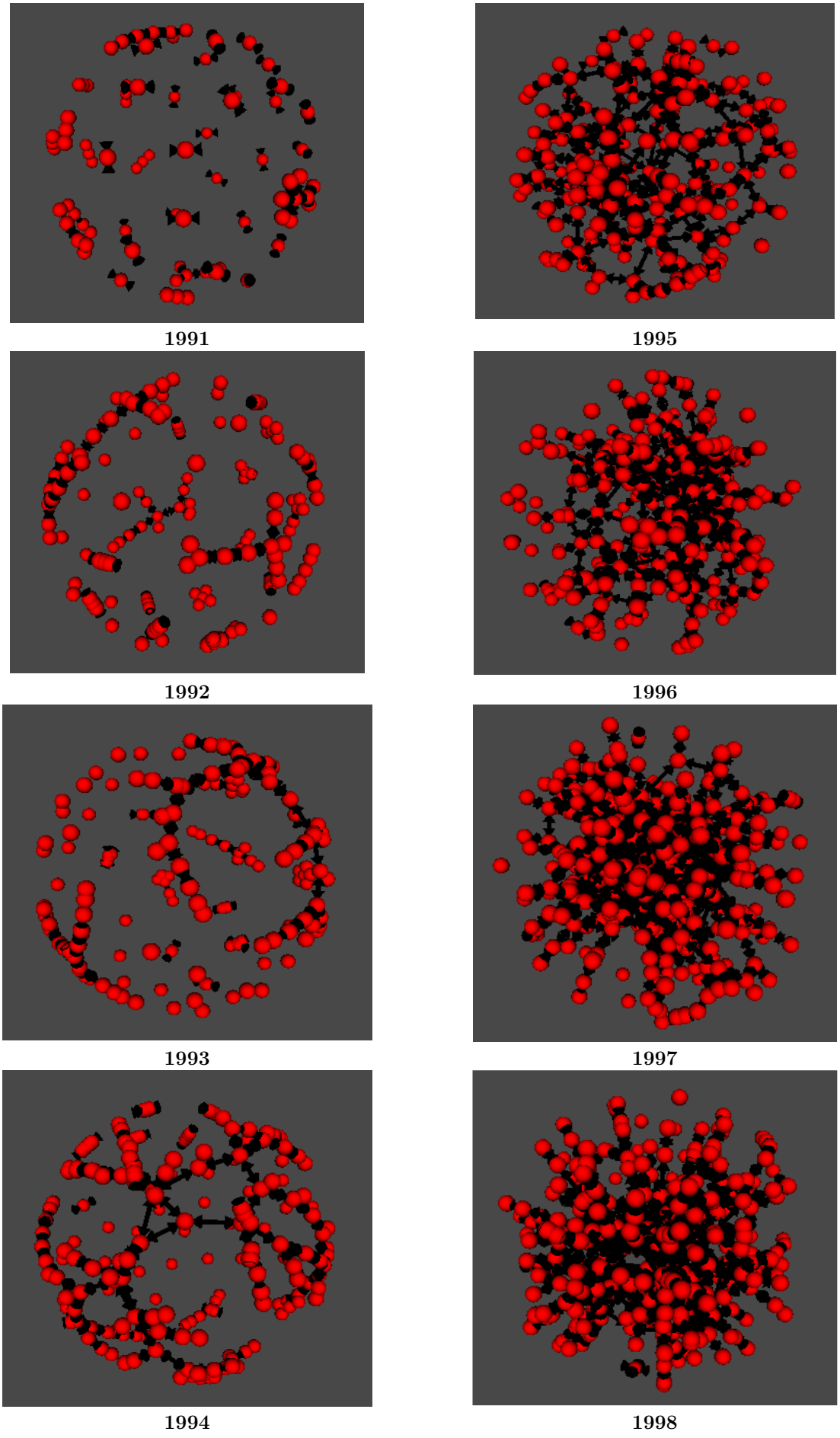

Figure 3: Inter–firm R&D 3D networks amongst cooperating companies in pharmaceutical biotechnology during the period 1991–1998; s*ource:* Recombinant Capital.

3 Actor–level Centrality and Network–level Centralization: A Descriptive Analysis

In the last section, we have revealed that the pharmaceutical biotechnology R&D network experienced an evolutionary change in its size and structure during the time period 1991–1998. In such a complex network environment, not only network structure, but also a firm's network position plays a crucial role in accessing relevant resources and information. In order to provide a quantitative analysis of a firm's structural position in a network, we have employed Social Network Analysis (SNA), which serves as the methodical analysis of social networks and complements the traditional mathematical techniques. One of the primary applications in the SNA is the identification of the "most important" players in a social network. The players who are most important are usually located in central positions within the network, which can be quantified by various centrality measures (Wasserman and Faust, 1994). The three most widely used centrality indicators are degree, closeness and betweenness, representing different degrees to which a player is capable to extract value from his network. These centrality measures of the player can be aggregated over all actors within the network to obtain the measures of network–level centralization, indicating how centralized the set of players is as a whole. In this section, following Wasserman and Faust (1994), we will discuss the conceptions of actor–level centrality and network–level centralization, and their applications to and implications for the pharmaceutical biotechnology industry. In accordance with Section 2, the data source that will be implemented in this section is Recombinant Capital database and the chosen time period is 1991–1998. The software package for computing various network–related measures is Ucinet 6 (Borgatti *et al.*, 2002). Based on the actor–level centrality, the most important players in pharmaceutical biotechnology are defined in the time period 1991–1998. With the network visualization function included in Ucinet 6 (Borgatti *et al.*, 2002), a graph was drawn displaying the firm's network position and interactions in the pharmaceutical biotechnology network (Figure 4).

3.1 Degree

The most intuitive measure of actor–level centrality is degree, which is based on the idea that actors are central in a communication network if information can easily reach them. An actor with a high degree centrality possesses more contacts to obtain information and resources, and thus is located at a more central position than others. In contrast, an actor with low degrees, who appears to be less visible in the information flows, is peripheral in the network. Even if such an actor decides to leave the network or is isolated from the relational process, it would hardly have any impacts on the present connections. According to Wasserman and Faust (1994), a degree–centrality measure $C_D(n_i)$ for an individual actor should be the degree of the node $d(n_i)$, which is simply the number of an actor's direct neighbours. For comparing this measure across different sizes of networks, we normalize $C_D(n_i)$ by dividing the maximum possible value of degrees $g-1$, assuming the network size is g. Thus, the normalized actor–level degree centrality $C'_D(n_i)$ can be written as

$$C'_D(n_i) = \frac{d(n_i)}{g-1}. \tag{1}$$

This measure equals 1 at a maximum and attains the value of 0 at a minimum. In a directed network, we must distinguish between the number of arcs received by an actor (indegree) and the number of arcs sent (outdegree) (Knoke and Burt, 1983). However, this would not be the case in the inter–firm R&D network, since the cooperation between firms, especially in the high–tech sector, heavily depends on mutual exchanges of technological innovation and knowledge. As a result, a network comprising cooperating companies is undirected and each firm is simply characterized by its degree. The higher the degree of a firm, the larger and quicker information will reach this firm, and the more central is this firm.

In accordance with Wasserman and Faust (1994), the actor–level degree centrality measure can be aggregated across all actors to obtain degree–based network centralization. This aggregated index, which indicates the level of the entire set of actors, can be defined as

$$C_D = \frac{\sum_{i=1}^{g}\left[C_D(n^*) - C_D(n_i)\right]}{g^2 - 3g + 2}, \tag{2}$$

where $C_D(n_i)$ in the numerator denotes the g actor degree indices, $C_D(n^*)$ denotes the largest observed value, and the denominator[3] of $g^2 - 3g + 2$ is actually the maximum sum of the differences in actor degree centrality. This maximum difference sum occurs only for the star network, since the star network is the most centralized network and has the maximum degree variation. Hence, the degree centralization in the entire network can be interpreted as the variation in the actor's degree in the observed network divided by the degree variation of a star network of the same size (Nooy *et al.*, 2005). It is also a measure of the dispersion of the actor's degree indices, since it compares each actor index to the maximum attained value (Wasserman and Faust 1994). This index varies from 0 to 1, with 0 indicating that all actor degrees are equal, and 1 indicating that one actor is connected to all other $g-1$ actors and all other actors interact only with this single central actor.

Table 1 provides the normalized degree–based network descriptive statistics in pharmaceutical biotechnology over the period of the study. As it shows, the mean of normalized actor–level degree centrality decreases steadily during the time period 1991–1998. This is because the network size, which serves as part of the denominator in the normalized degree index, increased dramatically over time (Figure 2). As for single company's normalized degree centrality, we can see from Table 4 that Schering Plough, Affymetrix, Pfizer and SmithKline Beecham are each characterized by the highest normalized actor degree, which contributes to the judgement that they are regarded as the most central players in time period 1991–1998. Other firms which share the information with these four companies seem to distribute the information to others (Figure 4), possibly because they recognize their central positions, and consider it worthwhile to influence other firms in the network. In terms of degree–based network centralization in the pharmaceutical biotechnology industry, the observed value is rather low (Table 1). This value declines from 4.43% in 1991 to 2.17% in 1993 before reaching a peak of 4.63% in 1997, and then sharply decreases to 2.91% in 1998. Due to this low amount of concentration in the whole network during the time period 1991–1998, the power of individual firms does not vary much. This shows that the overall positional advantages based on degrees tend to be relatively equally distributed in the pharmaceutical biotechnology network.

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[3] If the network is a star, the maximum value of $C_D(n^*)$ is $g-1$ for an actor and $C_D(n_i) = 1$, and thus the maximum sum of differences for $g-1$ comparisons is $\left[(g-1)-1\right](g-1) = (g-2)(g-1) = g^2 - 3g + 2$.

3.2 Closeness

The actor–level closeness centrality, which is based on the graphical distance in a network, measures how close an actor is to all the other actors within the network (Wasserman and Faust, 1994). Unlike degree centrality, which only accounts for the connections to immediate neighbours, closeness centrality takes both, direct connections and indirect connections, into consideration. An actor with high closeness centrality scores can reach all the network members in a minimum number of steps and interact with them efficiently without going through many intermediaries, and consequently has more opportunities for information exchange and resource transactions. This centrality index is measured as a function of geodesic distances but inversely correlated to the distance: when geodesic distance increases, the closeness centrality scores decrease. Let $d(n_i, n_j)$ denote the geodesic distance (shortest path) between the actors i and j, the closeness centrality of an actor, $C_C(n_i)$, can then be expressed as the inverse of the sum of geodesic distances from actor i to all other actors in the network, $\left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1}$. For comparisons of indices across different sizes of network, we normalize this closeness index through multiplying the inverse of the distance by the maximum possible distance $g-1$, which can thus be defined as

$$C'_C(n_i) = (g-1)\left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1} \quad \text{where } j \neq i. \tag{3}$$

The normalized closeness index ranges between 0 and 1, reaching 1 when the actor is maximally close to all other actors. However, if a network is not strongly connected, the closeness centrality cannot be calculated due to the infinite distance between disconnected actors. This is the case in the pharmaceutical biotechnology R&D network, so instead of using closeness index above, normalized actor's closeness centrality can be calculated with standardized reach closeness, which is an index of reach distance from each actor to all others adjusted to the network size. A smaller reach distance yields a higher closeness centrality score.

The network–level of closeness centralization is analogous to the degree centralization in that we compare the amount of variation in the closeness centrality

scores of the actors with the variation in closeness centrality in a star–network of the same size. The general network closeness index is based on the normalized actor–level closeness centrality and can be expressed as

$$C_C = \frac{\sum_{i=1}^{g}\left[C'_C(n^*) - C'_C(n_i)\right]}{(g^2 - 3g + 2)/(2g - 3)}, \tag{4}$$

where $C'_C(n^*)$ is the largest normalized actor closeness in the set of actors and the denominator[4] of $(g^2 - 3g + 2)/(2g - 3)$ is the maximum difference sum of the actor closeness centrality. The closeness centralization ranges from 0 to 1, with the index attaining its minimum of 0 when the lengths of geodesic distances are all equal. Unfortunately, the closeness–based network centralization in the pharmaceutical biotechnology industry cannot be computed since the star network does not necessarily have the highest variation in closeness centrality scores if the network is not strongly connected. However, descriptive statistics, as provided in Table 2, also disclose the closeness–based information at the level of the whole network.

It can be seen from Table 2 that the average normalized centrality of reach closeness remains constant during the period 1991 to 1993 and from 1994 on it raises steadily, reaching a peak value of 0.18 in 1997 and then declining to 0.15 in 1998. The gap between the minimum and maximum value of normalized reach closeness centrality is very small. This low variation results in the overall small value of standard deviations.

In terms of the specific actor's centrality, we could take a look at Table 4, which shows that Schering Plough, Incyte Pharmaceuticals, Bayer and SmithKline Beecham have high centrality scores on reach closeness in the time period 1991–1998. Those firms with the highest closeness scores are able to reach the information in the network more easily and quickly since they are closer to all other firms. But if one of them leaves the network, this will strongly impact the overall network structure. If Schering

[4] The maximum possible closeness occurs when an actor is at a distance of 1 from all other actors, and all other actors are at a distance of 1 from the center and at a distance of 2 from each other. Therefore, the closeness sum for each is $(g-1)/\left[1+2(g-2)\right] = (g-1)/(2g-3)$ and yields a difference of $1-(g-1)/(2g-3) = (g-2)/(2g-3)$. Thus, for $g-1$ comparisons, the maximum possible difference is $(g-1)g - 2/(2g-3) = (g^2-3g+2)/(2g-3)$.

Plough, Incyte Pharmaceuticals, Bayer and SmithKline Beecham (Figure 4), for instance, quits from the R&D network, the network structure and the pattern of the knowledge flow in pharmaceutical biotechnology will dramatically change.

3.3 Betweenness

Degree and closeness centrality that have been applied earlier are mainly based on the reachability of an actor within a network. Another factor that could be considered for centrality is betweenness, which regards an actor as more central when he is more important as an intermediary between pairs of other actors in the communication network. More specifically, a central actor occupying a "between" position could control resource flow and coordinate information between network members that otherwise do not have a connection. The more network members depend on this actor to make connections with others, the more important the role of this actor is in the information flow. Thus, an actor with a high betweenness centrality score is strongly needed in a network as a link in the chains of contacts that helps distribute information. In accordance with Wasserman and Faust (1994), let g_{jk} denote the number of geodesics paths between actors j and k, $g_{jk}(n_i)$ denote the number of geodesics between actors j and k that pass through actor i, the actor–level betweenness centrality $C_B(n_i)$ can thus be expressed as $\sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}}$, which is the sum of probability of an actor i standing along any geodesics[5] that all pairs of actors in the network have selected. As with the other centrality standardizations, we normalize the betweenness centrality scores by dividing $C_B(n_i)$ by the maximum possible betweenness[6] $(g^2 - 3g + 2)/2$ so that it can be easily compared to the other actor

[5] According to Wasserman and Faust (1994), $1/g_{jk}$ is the probability that a message passes along any one of the actor j and k, and thus $g_{jk}(n_i)/g_{jk}$ is the probability that actor i falls on a randomly selected geodesic linking actor j and k, under the assumption that geodesics are equally likely to be chosen for the path.

[6] Since maximum betweenness centrality can be obtained only when there is an actor n_i that falls on all geodesics of length greater than one, the upper limit of $C_B(n_i)$ is simply to compute the number of paths connecting pairs of actors where n_i falls on the path between them. We know if all actors are

indices as well as across different sizes of networks. This normalized actor–level betweenness for n_i is then given by

$$C'_B(n_i) = \frac{\sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}}}{(g^2 - 3g + 2)/2} \quad \text{for } i \neq j \neq k\,. \tag{5}$$

Compared to the closeness index, the betweenness centrality has the advantage that it can be computed even if the network is not strongly connected. This index takes a minimum value of 0 and a maximum of 1 when the actor i falls on all geodesics.

Analogous to degree and closeness measure, the actor–level betweenness can be aggregated across actors to obtain the overall network centralization index, which allows us to compare different networks with respect to the heterogeneity of the actor's betweenness. According to Wasserman and Faust (1994), betweenness centralization is simply the variation in the betweenness centrality scores of actors divided by the maximum variation in betweenness centrality scores possible in a network of the same size:

$$C_B = \frac{\sum_{i=1}^{g}\left[C_B(n^*) - C_B(n_i)\right]}{(g^3 - 4g^2 + 5g - 2)/2}, \tag{6}$$

where $C_B(n^*)$ is the largest realized value of the betweenness centrality $C_B(n_i)$. The denominator $(g^3 - 4g^2 + 5g - 2)/2$ is the maximum difference sum of the actor–level betweenness centrality[7]. This index reaches its maximum value of 1 in a star network

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reachable, there are $g(g-1)/2$ paths connecting the unordered pairs in the network and of these, $g-1$ are connected to n_i, so the maximum betweenness centrality is then $\max C_B(n_i) = g(g-1)/2 - (g-1) = (g-1)(g-2)/2 = (g^2 - 3g + 2)/2$.

[7] According to Freeman (1979), the betweenness-based network centralization index is defined as the average differences between the relative centrality of the most central actor and that of all other actors. This calculation of standardized indices can be made equivalently with the network centralization based on betweenness as follows:

$$C_B = \frac{\sum_{i=1}^{g}\left[\frac{C_B(n^*)}{(g-1)(g-2)/2} - \frac{C_B(n_i)}{(g-1)(g-2)/2}\right]}{g-1} = \frac{2\sum_{i=1}^{g}\left[\frac{C_B(n^*)}{g^2-3g+2} - \frac{C_B(n_i)}{g^2-3g+2}\right]}{g-1} = \frac{2\sum_{i=1}^{g}\left[C_B(n^*) - C_B(n_i)\right]}{(g-1)(g^2-3g+2)} = \frac{\sum_{i=1}^{g}\left[C_B(n^*) - C_B(n_i)\right]}{(g^3 - 4g^2 + 5g - 2)/2}.$$

and reaches its minimum value of 0 if all actors in the network are equal in betweenness.

As can be seen in Table 3, the average value of normalized actor–level betweenness centrality in the pharmaceutical biotechnology industry follows an increasing trend from 1991 to 1994, reaching a peak value of 1.26 in 1994, whereas it appears to have a decreasing trend from 1994 on, declining to 0.64 in 1998. The maximum value of this centrality substantially increases from 0.43 in 1991 to 25.44 in 1995 before declining to 11.62 in 1996, and then it remains relatively stable until 1998. In terms of the specific company's normalized betweenness centrality, Schering Plough, which is the most central firm in the time period 1991–1998 regarding its highest degree centrality and closeness centrality, appears to be the most important firm as well when betweenness centrality is taken into account (Table 4). It can be seen from Figure 4 that Schering Plough plays an important role in the communication between Du Pont and Incyte Pharmaceuticals. If Schering Plough fails to pass on information, Du Pont will not reach Incyte Pharmaceuticals any more. In contrast, University of British Columbia, Children's and Women's Health Center of British Columbia hardly fall on any geodesic pathways between other pairs of firms. They only form a small research cluster with Base4 Bioinformatics at an isolated network position that seems to be nearly disconnected from knowledge generated outside this small cluster (Figure 4).

With regard to the betweenness–based network centralization, the centralization score dramatically increases from 0.42% in 1991 to 24.37% in 1995 before decreasing to 10.42% in 1997, and it slightly increases again to 11.17% in 1998 (Table 3). These network centralization values are rather low in the time period 1991 to 1993, and in 1991 and 1992, they are even lower than the values of the degree–based centralization index (Table 1). However, in contrast to the low value of degree–based network centralization during the period 1994 to 1998, the observed values in betweenness index with the peak value of 24.37% in 1995 are moderately high. This indicates that even though most firms in the pharmaceutical biotechnology sector are linked to the R&D network, some of them are more active than others.

3.4 Most Important Players

Based on the actor–level centrality measures that have been discussed above, there are three advantages for a firm to be the most important player in a network: First of all, they have more contacts than others, that is, they have more opportunities to obtain information and resources than other firms within a network. Secondly, when they are at a more central position in the network, they are more reachable by other firms at shorter path lengths. This structural advantage allows them to interact with other firms quickly and access information more rapidly. The third advantage is that they are situated on more pathways between other pairs of firms. This allows them to broker contracts among other firms or prevent contracts by isolating other firms (Gulati, 1999; Wasserman and Faust, 1994). In Table 4, we have chosen the 40 most important players from the pharmaceutical biotechnology network in the time period 1991–1998 based on their centrality scores of degree, closeness and betweenness. In order to visualize a firm's position and interactions in the network, a graph containing 186 companies[8] in the pharmaceutical biotechnology R&D network in the period 1991–1998 is presented (Figure 4). In this graph, the size of the node is adjusted by firm's degree centrality: the bigger node in Figure 4 represents the firm with higher degree centrality. Particularly, the nodes of "important" and "non–important" companies are depicted by different colours: red nodes for the 40 most important firms (Table 4) and blue node for the remaining companies (Figure 4).

As Table 4 shows, 10% of the 40 most important companies in the pharmaceutical biotechnology sector engage in commerce on both pharmaceutics and biotech, such as Corixa, Millennium Pharmaceuticals and Roche. The business of Amersham Pharmacia Biotech, as its name shows, is also twofold, since it results from a merger between pharmaceutical and biotech companies (i.e., UK–based Amersham International, Sweden–based Pharmacia Biotech and Norway–based Nycomed). Biotechnology firms account for 37.5%, while pharmaceutical companies account for 52.5% of the most important players of the pharmaceutical biotechnology sector (Table 4), which may imply that pharmaceutical firms play a more dominant role than biotechnology firms during 1991–1998. As can be seen in Table 4, the number one of the 40 most important

[8] Due to a large number of pharmaceutical biotechnology companies that engaged in partnerships during the time period 1991–1998, it was impossible to draw the entire R&D network. For this reason, we have shrunk the network by removing firms with a degree centrality of less than 5.

players is the US–based pharmaceutical company Schering Plough (marked in bold) with the highest centrality score on all measures of degree, closeness and betweenness in the research network. Other large established pharmaceutical companies, such as Pfizer and SmithKline Beckman have also become nodal network players in the 1990s that are embedded in dense local research clusters with many participating partners (Figure 4). An important driving force here is possibly the second wave of the molecular biological revolution: genetic engineering, which opened up completely new areas for innovation (Gilsing *et al.*, 2008).

The trend of the development in the pharmaceutical biotechnology network during the 1990s, however, is in contrast to that during the 1980s, as some authors proposed. Roijakkers and Hagedoorn (2006) indicated that with the emergence of biotechnology during the 1980s, the small entrepreneurial biotechnological firms had a leading role in the inter–firm R&D network. Also, they formed important bridges between research sub–networks surrounding large pharmaceutical companies. But in the 1990s, as Figure 4 shows, the importance of these biotechnology firms decreased in the research network in comparison to the role of large pharmaceutical companies. Also, during this period, the role of these biotechnology firms as bridges between major sub–networks became less prominent. Overall, large pharmaceutical companies have developed into dominant star players with multiple partnerships while occupying central roles in the R&D network during 1991–1998. Nevertheless, in a long–term perspective, the entrepreneurial biotechnology firms will remain crucial partners for pharmaceutical companies due to the mutual dependence between the pharmaceutical industry and the biotechnology sector (Roijakkers, 2003).

The section above provides insights into the development of inter–firm pharmaceutical biotechnology R&D networks over time by evaluating the importance of network participants and research cooperation at the general network level with descriptive statistics based on the conceptions and measures of actor–level centrality and network–level centralization. In the next section, we will apply the econometrical techniques and Burt's (1992) "structural hole" theory to identify what actually determines a firm's centrality–based partnering capability in an inter–firm pharmaceutical biotechnology R&D network.

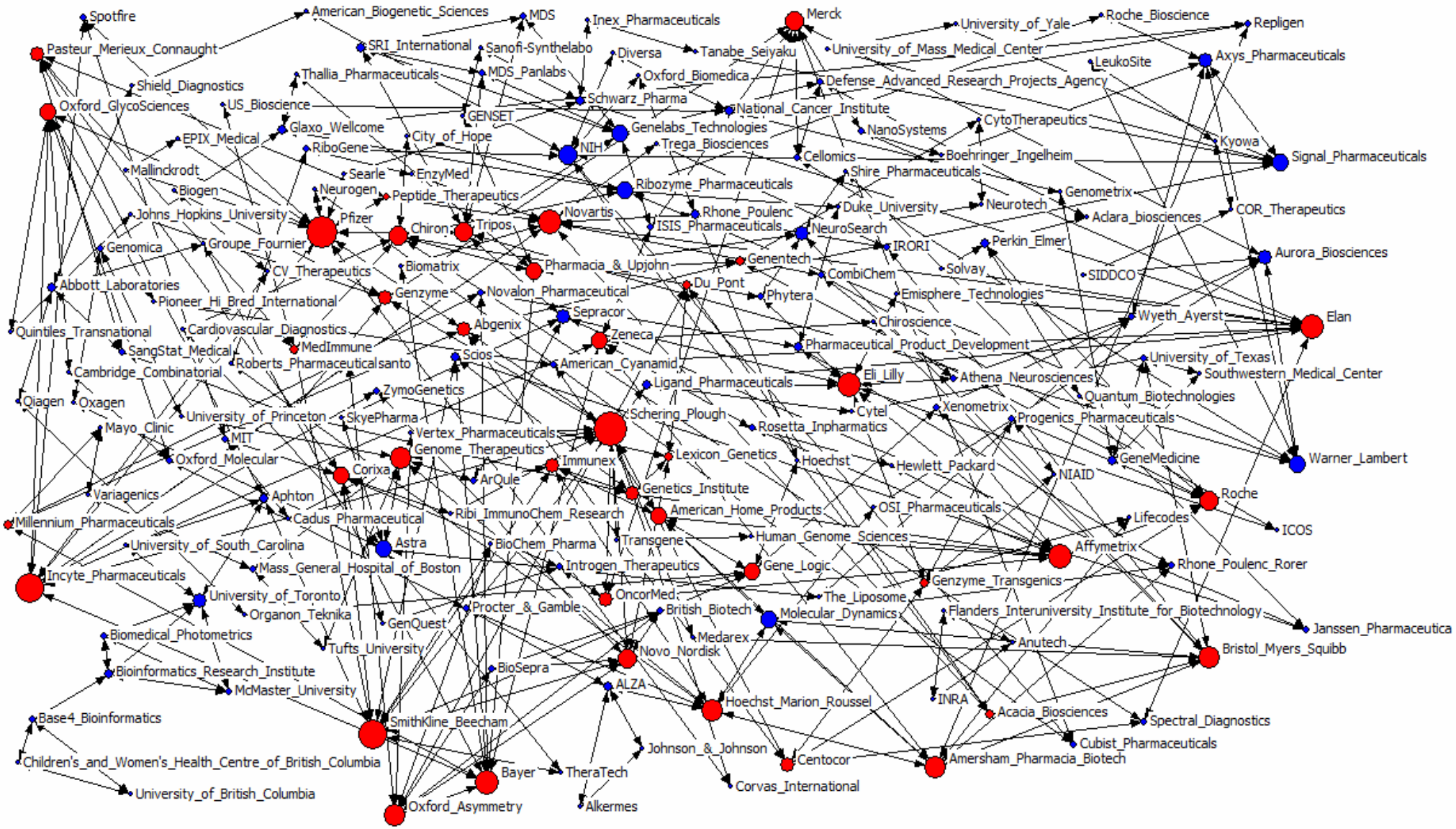

Figure 4: Inter–firm R&D network amongst cooperating companies in pharmaceutical biotechnology, 1991–1998; *source*: Recombinant Capital.

4 Determinants of Firm's Centrality–based Network Capability: An Empirical Perspective

4.1 Hypotheses

In the dynamic and fiercely competitive pharmaceutical biotechnology industry, it is important for companies to keep pace with constantly developing innovations and meet changing customers' needs. The success of a company is influenced by its ability to access diversified contacts with a variety of other firms to develop research resources. As a result, choosing suitable partners becomes crucial for improving a firm's position in an inter–firm network. As indicated by the social network literature, the partner selecting skills of a firm are characterized by efficiency, which refers to the idea of avoiding the maintenance of redundant partnerships that carry little additional information (Granovetter, 1973; Burt, 1992). Redundant contacts not only provide redundant information, but also generate costs from building and maintaining them (Gulati, 1995 and 1999; Kale and Singh, 1999). However, if they were optimally avoided, firms could save the time and resources invested in unnecessary duplication of contacts and could use more resources to access valuable information from useful partnerships. Hence, strategic firms should carefully determine the additional value brought by new contacts and build up a non–duplicative network to gain adequate transfer of information. Within such an efficient network firms also have the advantage to create brokerage positions with control over information flows between other partners, thus attaining a central position in the network. Therefore, it is expected that a company with higher efficiency level would have larger centrality–based partnering capability.

Hypothesis 1: In the pharmaceutical biotechnology network, the level of efficiency of a firm is positively correlated with its centrality–based partnering capability.

The inter–firm cooperation between pharmaceutical companies and biotechnology firms can also be explained by resource dependence theory (Pfeffer and Nowak, 1976). According to this resource–based view, different firms can be seen as different bundles

of resources. If a firm wants to exploit its stock of resources, it will be necessary to acquire complementary resources externally (Grant, 1991). This is especially the case in the pharmaceutical biotechnology industry. Alongside the usual difficulties of star–up companies, the biotechnology firms need large amounts of capital to fund costly research, market expertises and experiences with the regulatory approval process (Powell, 1998). Allying with large established pharmaceutical companies could provide them with a set of organizational capabilities and resources that they are lacking. Although the large pharmaceutical companies play a dominant role in the commercialization process, they often have been unable to create an internal research environment that would foster constant discovery and innovation. The biotechnology firms, however, could make up for this lack of internal capabilities and resources through various kinds of partnerships (Arora and Gambardelly, 1994; Powell *et al.*, 1996). As outlined above, there is a certain degree of mutual dependence developed in the R&D relationship between pharmaceutical companies and biotechnology firms. In this industry, a company with more dependency on complementary resources would have more opportunities to access multiple sources from the network and develop their innovative capabilities, and in turn, increase its ability to strategically place itself in a central network position among other firms. Thus, one might expect that firms with more dependency on complementary resources would have larger centrality–based partnering capability.

Hypothesis 2: In the pharmaceutical biotechnology network, a firm's dependency on its complementary resources is positively correlated with its centrality–based partnering capability.

Another feature of the pharmaceutical biotechnology industry is that it follows rapid unforeseen technological changes that have a major effect on the management of innovation within firms and also on their partnering activities (Eisenhardt and Bird–Schoonhoven, 1996; Hagedoorn, 1993). It requires firms to identify new projects quickly and to launch them into the market strategically. This ability could be improved by a firm's experiences at managing inter–firm partnership. Firms with more partnering experiences may increase their specific knowledge about when to form a partnership, whom to partner with, and how to value external sources of technological knowledge, and in turn, they could effectively react to unexpected events that may occur in its

links to other firms and locate themselves in information–rich positions which are central in the network (Gulati, 1999; Levinthal and March, 1993). In other words, the development of a firm's experience at managing partnerships enables it to find a well–developed network position and thus increase its centrality–based partnering capability. Furthermore, more experiences at managing partnerships allow the firm to build up its reputation as skilled and knowledgeable partner. This makes it an attractive partner for other companies in the network, and hence the firm could better access sources from others and gain competitive advantages to obtain a central network position (Brass *et al.*, 1998; Hagedoorn *et al.*, 2006). This leads to the next hypothesis.

Hypothesis 3: In the pharmaceutical biotechnology network, the partnering experiences of a firm are positively correlated with its centrality–based partnering capability.

4.2 Research Methods

4.2.1 Research Setting

The network environment that is chosen here is the global pharmaceutical biotechnology sector. In this high–tech sector there is an abundance of inter–firm partnerships and substantial R&D partnering activities (Powell, 1998; Walker *et al.*, 1997). The sector comprises new biotechnology firms dedicated to commercializing the new technology such as Genentech, and large pharmaceutical companies such as Eli Lilly that participate in biotechnology for drug development and commercialization (Rothaermel, 2000). R&D partnerships are an important form of inter–firm collaboration in this sector (Hagedoorn and Roijakkers, 2002). As described below, there are two main reasons why the pharmaceutical biotechnology industry is interesting for the analysis from the perspective of inter–firm strategic networking in the context of R&D partnerships.

First of all, the pharmaceutical biotechnology industry provides a prime example for studying the development of inter–firm R&D collaboration. The historical background of this sector is interesting and unique. During the 1950s and 1960s, large pharmaceutical companies mainly followed a "going–it–alone" research strategy so that inter–firm R&D collaboration did not play a crucial role (Roijakkers, 2003). However,

along with the biotechnology revolution in the 1970s, the pharmaceutical industry experienced a dramatic change in knowledge and technology developments and was to some extent forced to change their research strategies to include a great variety of R&D partnerships (Roijakkers, 2003). Later, in the 1980s and 1990s, technological collaboration continued to be a significant feature in the pharmaceutical biotechnology industry. Secondly, the cooperation formed in the pharmaceutical biotechnology industry has led to the emergence of a strong dual market structure, which is developed by large established pharmaceutical companies and small research–intensive biotechnology firms (Powell *et al.*, 2005; Saviotti, 1998). The capabilities and resources of these two groups of firms were complementary, resulting in numerous inter–firm partnerships in the R&D network.

In this research setting, balanced panel data was applied, since a panel data set follows a given sample of cases over time (in this case, pharmaceutical biotechnology companies), thus providing multiple observations on each of the cases in the sample (Baltagi, 1995). Based on actor–level centrality measures (as discussed in Section 3), only those companies, which were considered to be the most important players in the pharmaceutical biotechnology sector during the period 1991–1998 (Table 4 in Section 3), were selected. However, in the empirical setting, the time period was shortened to 1995–1998 because from the mid–1990s, a new pattern of innovation emerged in the pharmaceutical biotechnology sector where innovation was largely concentrated in dense networks of inter–firm R&D partnerships (Roijakkers, 2003). Therefore, the sample that was analysed comprised the 40 most important pharmaceutical biotechnology companies that were cooperating through multiple partnerships during the period 1995–1998 leading to 160 observations.

4.2.2 Variables

The dependent variable that was used to describe a firm's partnering centrality–based capability within a network is the logarithm form of the betweenness centrality, which indicates the percentage change in betweenness centrality as an extra unit change in the explanatory variable. As shown in Section 3, the betweenness measure of centrality is based on the idea that the player positions itself on the shortest path between other pairs of players in the network and it regards a firm's capacity to

control information exchange between other companies in a network. The more firms depend on a focal firm to make linkages with other firms, the more power and influence this focal firm gains. In this study, normalized centrality measure of betweenness was used because an absolute measure of betweenness cannot be used to compare firms' centralities for different sizes of network. This normalized measure ranges between 0 and 1, with higher scores indicating greater firm centrality in a network relative to other network partners.

Two of the independent variables are based on the network theory of "structural hole" proposed by Burt (1992). According to this author, "structural hole" indicates a relationship of non–redundancy between two contacts. By bridging structural holes, the player can obtain non–redundant information and in turn occupy an advantageous position within the network. In other words, network benefits accrue to those actors, who broker connections between unconnected groups of players. For instance, if a company knows a lot of other firms which are disconnected from each other, it would have the chance to detect and develop brokerage opportunities between them. However, if all other firms are all tightly connected, broker opportunities would be difficult to attain. There are mainly two conceptions from the theory of "structural hole" that could be applied in the current study: efficiency size and hierarchy, both of which are well–established measures in the inter–firm network literature (see Abbasi and Altmann, 2010; Buskens and Rijt, 2008; Chung and Hossain, 2008; Hagendoorn *et al.*, 2006; Okoli and Oh, 2007; Roijakkers, 2003).

According to social network theory (Burt, 1992), a firm's efficiency can be indicated by its efficiency size, which measures what proportion of a focal firm's contacts to its partners is non–redundant. Hence, the efficiency size of a focal firm i is the sum of the non–redundant portion of i's connections with all other firms in the network divided by the number of its partnerships, N. It can be normally defined as

$$Efficiency_i = \frac{1}{N}\sum_j \left[1 - \sum_q p_{iq} m_{jq}\right], \; q \neq i, j \tag{7}$$

where $p_{iq} m_{jq}$ denotes that the information access, timing, and referrals the focal firm i gets through its contact j are redundant to the extent that firm i has a substantial investment of time and energy in a relationship with another partner, q, to whom its

partner j has a strong relation[9]. Aggregating $p_{iq}m_{jq}$ across all contacts q measures the portion of i's relationship with j that is redundant to i's relations with its other primary contacts. Thus, 1 minus this expression is the non–redundant portion of the relationship. With respect to the "structural hole" theory, the sum across relationships of the non–redundant portion divided by the number of the focal firm i's total links is the normalized number of non–redundant contacts in firm i's network. This efficiency ratio varies from a minimum approaching 0, indicating high contact redundancy which implies low efficiency, to a maximum of 1, indicating that every contact in the network is non–redundant.

Efficiency size (as discussed above) can be used to indicate the efficiency level of a focal firm's network and therefore is a suitable measure for Hypothesis 1. To test the prediction of Hypothesis 2, a hierarchy measure was used in this study, which is in fact an adjustment of a constraint measure. Constraint indicates the degree of dependency in the partnerships of a firm. In other words, it measures the extent to which a firm has partners that cooperate intensely among themselves (Hanneman and Riddle, 2005). For instance, if a focal firm i's partners all have many potential partners on their own, the constraint posed on firm i is high. However, if the local network of firm i is sparsely linked so that its partners do not have other alternatives in the neighbourhood, the degree of constraint posed on firm i would be low. According to Burt (1992), constraint refers to the focal firm i's investment in reaching partner j multiplied by the lack of structural holes around j with which firm i could negotiate a favourable rate of return on investment. Investment is defined as the proportion of the focal firm i's network time and energy that leads to partner j and the lack of holes around j. Their product defines partner j's constraint on firm i:

$$c_{ij} = (i\text{'s investment in reaching } j)(\text{lack of holes around } j) = \left(p_{ij} + \sum_q p_{iq}p_{qj}\right)^2 O_j, i \neq q \neq j \quad (8)$$

[9] p_{iq} is the proportion of firm i's network time and energy invested in the relationship with partner q (interaction with q divided by the sum of firm i's relations), $p_{iq} = \left(z_{iq} + z_{qi}\right) \Big/ \left[\sum_j (z_{ij} + z_{ji})\right], i \neq j$, and m_{jq} denotes the marginal strength of partner j's relation with contact q (interaction with q divided by the strongest relation of j), $m_{jq} = (z_{jq} + z_{qj}) \big/ \max(z_{jk} + z_{kj}), j \neq k$, where z_{ij}, a general cell of matrix Z transformed from the dichotomized matrix, is the network variable measuring the strength of the relation from i to j (Burt, 1982).

and the aggregate constraint on firm i, $C = \sum_j c_{ij}$, is the sum of constraint from i's partnership with each of the N partners[10]. The partner–specific constraint ranges from a minimum of 0 to a maximum of 1, with 1 representing that j is the only partner of firm i and 0 representing that j has no partnership with firms with whom firm i could replace partner j (Burt, 1992).

Hierarchy, which describes the nature of the constraint on a focal firm, measures the important property of dependency to the extent that it indicates the inequality in the distribution of constraints on a focal firm across other firms in its neighbourhood (Hanneman and Riddle, 2005). If the total constraint on a focal firm is concentrated on a single other actor, the hierarchy measure will have a higher value. If the constraint results more equally from multiple companies in the focal firm's neighbourhood, hierarchy will be less. This hierarchy measure can be calculated using the following two–step procedure. First, for each partner j of firm i, the ratio of partner–specific constraint to the average level of constraint per partner $\frac{c_{ij}}{C/N}$ is computed, where C/N is the average constraint per partner. This ratio indicates how much one specific partner j is considered to be a more severe source of constraint to firm i than any of its other partners. In the next step, the Coleman–Theil disorder index is applied to compute the actual hierarchy measure. This method multiplies the sum of all partner–specific constraint ratios by its natural logarithm and divides the product by the maximum sum possible. Thus, the hierarchy measure of a focal firm i can be stated as

[10] $p_{iq}p_{qj}$ denotes that firm i's entrepreneurial opportunities are constrained to the extent that another of firm i's partner q, in whom firm i has invested a large proportion of his network time and energy, has invested heavily in a relationship with firm i's partner j. Aggregating $p_{iq}p_{qj}$ across all contacts q (excluding firm i) and adding i's direct connection with j defines firm i's investment in reaching partner j : $p_{ij} + \sum_q p_{iq}p_{qj}, q \neq i, j$. The lack of structural hole is measured as lack of holes around $j = \left(p_{ij} + \sum_q p_{iq}p_{qj} \right) O_j, i \neq q \neq j$ where O_j denotes the organization of players within the cluster around partner j so that it would be difficult to replace j by other partners in the cluster.

$$Hierarchy_i = \frac{\sum_j (\frac{c_{ij}}{C/N}) \ln(\frac{c_{ij}}{C/N})}{N \ln(N)} \quad (9)$$

This measure attains its minimum of 0 when constraint is the same for each partner of a firm, and reaches its maximum of 1 when all constraint is concentrated on a single partnership.

In order to examine Hypothesis 3, the experienced–based independent variable was computed. For this, the measure of number of inter–firm R&D partnerships of firms was used, since it could reflect the experience of the focal firm in cooperation with other firms. The more partnerships a focal firm has, the more cooperative experience it gains and the more it benefits from the inter–firm cooperation between companies.

Based on the inter–firm network literature (e.g., Hagendoorn *et al.*, 2006; Roijakkers, 2003), indicators of duration and time effects were applied as control variables in this study. In the chosen model, the time since the last R&D partnership was established is controlled. For this, the variable "duration" was constructed to track the time elapsed since the former partnership of firms and set to 0 at the outset. Besides, the presence of a particular trend in new R&D partnership formation over time could potentially bias the results. To control possible effects of time, the year dummies "time effect (1995–1998)" were included by using the year 1995 as reference.

Dependent variable, efficiency measure, hierarchy measure and the experience–based independent variable were all calculated with Ucinet 6 (Borgatti *et al.*, 2002). The basic source of information for Ucinet 6 was the Recombinant Capital database, which is a binary, symmetric adjacency matrix containing the partnerships between the firms in a network. Separate matrices for each year were calculated to obtain the value of the network related measures for certain chosen companies.

4.2.3 Statistical Methods

As stated in Hypothesis 1, a firm's efficiency is predicted to raise its centrality–based capacity in the pharmaceutical biotechnology industry. A firm with higher efficiency to choose collaboration partners may have a larger capability to place itself in a central position within the network. In this relationship, from the econometrics

point of view, it is necessary to consider the potential existence of "reverse causality", where the efficiency of a company is likely determined simultaneously along with its centrality–based partnering capability. Some authors (e.g., Hagedoorn and Duysters, 2002; Hagedoorn *et al.*, 2006) suggest that a company with a central position in an inter–firm network would have more information about the position of other firms in the network and their information flows, which enables it to use its centrality–based capability to delete duplicating partners, thus gaining high efficiency. Therefore, firm's ability to obtain a central position within the network may partially determine the level of its efficiency to select suitable partnerships. If the traditional ordinary least squares (OLS) method in a linear regression model[11]:

$$y_i = X_i \beta + u_i \tag{10}$$

is adopted in the presence of reverse causality between firm's efficiency and its centrality–based capability, it is highly likely that this model will be inconsistent, meaning that due to the endogeneity of a firm's efficiency, changes in its efficiency level are associated not only with changes in the dependent variable of firm's centrality–based capability but also with changes in the error term of the model (see equation (10)). What is needed in this case is typically a method to generate only exogenous variation for firm's efficiency level. An obvious way to do this is through an experiment. The application of instrumental variables (IV) method provides a way to obtain consistent parameter estimates if suitable instruments exist. There are various instrumental variable methods that could be applied to a model's endogeneity problems. In this study, the two–stage least squares (2SLS) and the optimal generalized method of moments (GMM) were used, the latter of which was named also after the two–step feasible efficient GMM.

The 2SLS estimator, as its name indicates, is obtained by two consecutive OLS regressions: In the first stage, the fitted value of a firm's efficiency is obtained from the OLS regression of the firm's efficiency on 1, included explanatory variables and instrumental variables. In the second stage, we run another regression by OLS of dependent variable of the firm's centrality–based capability on 1, included explanatory

[11] y_i denotes the centrality–based partnering capability of a focal firm i, X_i denotes the matrix of the regressors including firm's efficiency level and other explanatory variables, β is the coefficient estimator which ranges from 0 to 1, and u_i is the error term.

variables and fitted value of the firm's efficiency that was obtained in the first stage, which gives a consistent 2SLS estimator. Although the 2SLS estimator is consistent, it could be inefficient in the presence of heteroskedasticity, which indicates that the error terms do not have constant variance. This problem can be partially addressed through the use of robust standard errors in the 2SLS model, in which a consistent estimate of the variance–covariance matrix for the error term could be derived (Baum *et al.*, 2003 and 2007). Another solution, introduced by Hansen (1982), is the optimal GMM method, which makes use of the orthogonality conditions to allow for efficient estimation in the presence of heteroskedasticity of unknown form. If heteriskedasticity is indeed present, the optimal GMM estimator is more efficient than the 2SLS estimator, whereas if in fact the errors are homoskedastic, the 2SLS estimator would be more preferable than the estimator of optimal GMM (Angrist and Pischke, 2009; Cameron and Trivedi, 2005). For this reason, a test for the presence of heteroskedasticity is necessary for deciding whether the 2SLS model or the optimal GMM is called for. In the model that was chosen here, the presence of heteroskedasticity is not completely clear since the standard tests such as Breusch–Pagan/Godfrey/Cook–Weisberg and White/Koenker test statistics show that heteriskedasticity is present in the model, while the Pagan–Hall test statistic (Pagan and Hall, 1983) indicates the error terms are homoskedastic. Therefore, both 2SLS estimator and GMM estimator will be applied successively to the model. The results from the methods of 2SLS, 2SLS with robust standard errors and optimal GMM will be presented in this paper.

In order to better exhibit the methods that will be used in the research, 2SLS estimator and optimal GMM estimator will be given in their original matrix form as follows. We now consider the model in equation (10) again, where X presents a $n \times K$ matrix of regressors with n being the number of observations. As discussed above, firm's efficiency to select partnerships is considered to be endogenous, so we need to generate exogenous variation for firm's efficiency level by choosing a $n \times L$ matrix of instrumental variables Z. In this case, the number of instruments excluded from the equation exceeds the number of included endogenous variables ($L > K$), so the applied model is overidentified. 2SLS is a common procedure for overidentified model. Given a set of K instruments: $\hat{X} = Z'(Z'Z)^{-1}Z'X = P_Z X$ where P_Z denotes the projection matrix $Z(Z'Z)^{-1}Z'$, the 2SLS estimator can be written as $\hat{\beta}_{2SLS} = (\hat{X}'X)^{-1}\hat{X}'y = (X'P_Z X)^{-1}X'P_Z y$ (Cameron and Trivedi, 2005; Wooldridge, 2002).

The standard 2SLS estimator can be regarded as a special case of GMM estimator and under the exogeneity assumption of instrumental variable, $E(Z_i u_i) = 0$, we now shortly derive a linear GMM model. GMM requires that a certain number of moment conditions were specified for the model, such as L instruments generating a set of L moment conditions, $g_i(\hat{ß}) = Z_i'\hat{u}_i = Z_i'(y_i - X_i ß)$, where g_i is $L \times 1$ matrix. These moment conditions are functions of the model parameters and the data, such that their expectation is zero at the true values of the parameters: $E(g_i(ß)) = 0$. Since each of the L moment equations corresponds to a sample moment, we can write these L sample moments as $\overline{g}(\hat{ß}) = \frac{1}{n}\sum_{i=1}^{n} Z_i'(y_i - X_i\hat{ß}) = \frac{1}{n} Z'\hat{u}$ (Wooldridge, 2002). The GMM method then minimizes a certain norm of the sample averages of the moment conditions, $J(\hat{ß}) = n\overline{g}(\hat{ß})'W\overline{g}(\hat{ß})$ where W is a $L \times L$ symmetric weighting matrix (Angrist & Pischke, 2009). GMM estimator is consistent for any symmetric positive definite weighting matrix W, however, the efficiency of this estimator is not guaranteed for an arbitrary W, which possibly leads to an inefficient estimator in GMM. Hansen (1982) chooses optimal weighting matrix $W = S^{-1}$ (S is the covariance matrix of the moment conditions to produce the most efficient estimator) to produce the most efficient or optimal GMM estimator, which can be written as $\hat{ß}_{OGMM} = (X'Z\hat{S}^{-1}Z'X)^{-1}X'Z\hat{S}^{-1}Z'y$ (Cameron and Trivedi, 2005; Wooldridge, 2002).

Even when 2SLS and optimal GMM is judged to be the appropriate estimation technique, we may still question its validity in a given application. “Good instruments” should be both valid and relevant (Baum *et al.*, 2003). In order to evaluate the validity of the instruments, we may cast some lights on whether the instruments are independent from an unobservable error process in the context of an overidentified model. If orthogonality conditions were satisfied to the extent that instruments are uncorrelated with the error term, the instrumental variables would be valid. To test this validity of the instruments, we could make use of the overidentification test: In terms of GMM, the overidentifying restrictions may be tested via the commonly employed J statistic of Hansen (1982), while Sargan’s statistic (Sargan, 1958), which uses an estimate of the error variance from the IV or 2SLS regression with the full set of overidentifying restrictions, is largely used for 2SLS method. By computing the difference–in–Sargan test or difference–in–J statistics, the endogeneity test, which is essentially testing whether the instrumental variable method is required to estimate the

model, can be implemented (Baum *et al.*, 2003). This test is equivalent to estimating the same regression but treating the regressor as exogenous, and then testing the corresponding orthogonality conditions. The null hypothesis of this test is that the specified endogenous regressor can actually be treated as exogenous. To address the relevance of the instrumental variable, we need to consider whether the instruments are correlated with the endogenous regressor. If the instruments are both correlated with the endogenous variable and orthogonal to the error process, the 2SLS estimator or GMM estimator will be consistent. However, to ensure an indeed good performance of the IV estimator, it should be considered whether the instruments are weak. The concept of a weak instrument is that the correlations between the endogenous regressor and the excluded instruments are nonzero but small (Cameron and Trivedi, 2005). Thus, if low correlation exists between the instrument and the endogenous variable being instrumented, the model is said to be weakly identified. In order to test the presence of weak instruments, the Stock–Yogo test (Stock and Yogo, 2005), which makes use of F–statistic form of the Cragg and Donald (1993) statistic, is commonly carried out.

The statistical methods of 2SLS and GMM and the tests for "good instruments" that are discussed above can be implemented by using Stata 11 (StataCorp, 2009), which is a statistical software package for data management, data analysis, and graphics. In this study, the data that was computed with Ucinet 6 (Borgatti *et al.*, 2002) based on Recombinant Capital database (see Section 4.2.2) was imported into the software Stata, and processed with the relevant commands. In particular, the "ivreg2 package" was applied (Baum *et al.*, 2002), which provides the extension to Stata software and is a suitable package for the panel data.

4.2.4 Choice of Instrumental Variables

As discussed in Section 4.2.3, due to reverse causality, a firm's efficiency, which is likely to be endogenous, needs to be instrumented with exogenous variables. In order to generate sufficient exogenous variation, a few instruments were considered to solve the endogenous problem. One candidate for the instrument is the firm's clustering coefficient, which is calculated by the proportion of cooperation that exists between firms and its neighbourhood divided by the number of cooperation that could possibly

exist between them. This concept could be further interpreted as the probability of which two collaborated partners of one firm in the network are connected to each other (Cantner and Rake, 2011), which is simply an indicator of the density of a firm's local neighbourhood (Hanneman and Riddle, 2005). The clustering coefficient is likely to influence a firm's efficiency to choose partners in the sense that the dense contacts among a firm's partnerships may cause redundant information and consequently reduce a firm's efficiency. This instrument can be calculated with the software Ucinet 6 (Borgatti *et al.*, 2002). The second candidate for the instrument could be the sector dummy of biotechnology. The biotechnology driven by innovation and discovery is largely used in manifold industrial manufacturing processes. Its advanced technical process, which reduces the environmental impact, improves the process efficiency and lowers the production costs, has advantages over traditional pharmaceutical process (EU, 2007). In a study on the Canadian biotechnology industry, Baum *et al.* (2000) found that biotechnology firms that were better able to leverage alliances, in particular R&D alliances, grew at higher rates than others. Similar results were found in a comprehensive EU study on the biotechnology industry in Europe (EU, 2002). The question, whether the sector is biotechnology is important to the firm's efficiency, because the biotechnology firms with newly updated, non–redundant information could efficiently choose the suitable partners by themselves in a rapidly developing technological environment.

Besides, a firm's national–geographic origin may also influence its efficiency to the extent that firms from various countries may have different levels of efficiency in gaining technological information. For instance, in the US, biotechnology is characterised by a high degree of concentration of firms in a restricted number of geographic regions. A similar process of clustering has taken place across Europe, with examples such as the biotech–region Munich and the Medicon Valley shared by Sweden and Denmark. However, in comparison with the US company structure, the majority of European biotechnology clusters do not seem to be big enough to compete effectively with those in the US (EU, 2007). In order to control for these effects, a set of national origin dummies was considered: US, England, Germany, Denmark, Switzerland, Sweden and Ireland. Among these national dummies, US, Germany and Denmark indicate closer correlations to the efficiency of a firm. Therefore, these three country dummies were included into the instrumental variable list. Another candidate for the instrumental variable could be the firm's age, which can be simply calculated from the

firm's foundation year. Firm's age is related to the firm's efficiency in the way that older firms with a higher number of cooperative arrangements are more experienced in the industry than younger firms (Rothaermel, 2002). Hence, older firms are more likely to detect opportunities for building up non–redundant contacts in the network and are thus more efficient in choosing partnerships.

Therefore, clustering coefficient, firm's age, sector dummy of biotechnology, and national dummies of US, Germany and Denmark were used in this study as instrumental variables to generate exogenous variation for the firm's efficiency, which is considered to be endogenous. All these instruments are likely to influence a firm's efficiency level, but will not directly determine the dependent variable of a firm's centrality–based partnering capability.

In order to obtain data for instrumental variables, we collected information on the national origin, foundation year and industrial sector provided by each firm in our population. Various sources of information were used such as the Institute for Biotechnology Information (BioSpace, BioCentury, and Funding Universe), US Small Business Innovation Research (SBIR) / Small Business Technology Transfer (STTR), Bloomberg Businessweek and Washington Post's Linkages.

4.3 Results

Table 5 provides descriptive statistics of explanatory variables for the 160 observations in the sample and a correlation matrix. The variances were relatively low on all variables since the sample only represents the prominent firms in the pharmaceutical biotechnology industry over years, which would not cause huge data differences between observations. And as would be expected, the dependent variable (the logarithm form of betweenness centrality) was highly correlated with the normalized number of firm's partnerships. Table 6 displays the estimation results of instrumental variable panel models using Stata 11(StataCorp, 2009). In model 1 and model 2 the standard 2SLS procedure was used, in which the independent error terms are assumed to be homoskedastic, while in model 3 and model 4 the 2SLS estimator was also used but the error terms of the models are robust to heteroskedasticity. Optimal GMM method, which allows for efficient estimation in the presence of heteroskedasticity, was used for model 5 to model 7. It can be seen from Table 6 that

the p–value in the endogeneity test was less than 1% in all models, so we can reject the null hypothesis that the firm's efficiency may be treated as exogenous. Thus, firm's efficiency is endogenous and instrumental variable methods are the appropriate estimation technique in our setting. As Table 6 also shows, the p–values in the overidentification test for model 1—model 7 were all larger than 10%, hence, we cannot reject the null hypothesis that the instrumental variables are uncorrelated with the residuals, which implies the instrumental variables that we chose are valid. However, the F statistics in Stock–Yogo test (Stock and Yogo, 2005) suggest that these instrumental variables could probably be weak instruments and the models are therefore weakly instrumented.

In model 1, model 3 and model 5, we estimated firm's centrality–based partnering capability as a function of its efficiency level, its dependency on complementary resource, its experience at managing partnerships, its duration in the partnerships and time effects (1996–1998). As time effects of 1996 and 1998 did not seem to affect firm's ability to be central (see Table 6), we dropped both of them in model 2, model 4 and model 6. After dropping time effects of 1996 and 1998, firm's efficiency did not appear to significantly influence firm's partnering capability anymore in model 6, even though it exerted influence in model 5. So we reestimated model 6 by excluding the clustering coefficient and country dummy Denmark from the instrumental variable list. As a result, the significance level of firm's dependency on complementary resources changed from level 10% to 5%, and firm's efficiency had impact again on its centrality–based capability as shown in model 7 (Table 6). Also, as we respecified the instruments list, the p–value in the overidentification test became larger when comparing model 7 to model 6. With the same set of variables, the models using methods of 2SLS and 2SLS with robust standard errors had exactly the same coefficient estimates, but different standard errors due to the potential presence of heteroskedaticity. However, after we reestimated the overidentified model using the optimal GMM method, the coefficients' point estimated changed slightly and standard errors decreased (Table 6), which generally indicates the model to be more efficient.

We hypothesized that firm's efficiency level is expected to have a positive impact on firm's centrality–based network capability (Hypothesis 1). The estimates of the indicator for firm's efficiency (efficiency size) were positive and significantly different from zero in the 2SLS models, 2SLS with robust standard error models and also in the optimal GMM models (only model 5 and 7). Thus, the instrumental variable methods

provide evidences that support a firm's efficiency to choose suitable partners as an important factor to determine its centrality–based partnering capability. Hypothesis 2 argues that the more a firm is dependent on its complementary resources, the higher the centrality–based network capability of this firm is. Model 1—model 7 all present that the estimates of the indicator for dependency (hierarchy measure[12]) have a significant, negative effect on firm's betweenness centrality. So a firm's dependency on its complementary resources was identified in the present study as another crucial factor for determining a firm's centrality–based partnering capability. Hypothesis 3 predicted that a firm with more experiences at managing partnerships tend to have a larger centrality–based network capability. The estimates of the indicator for firm's partnering experiences (normalized number of firm's partnerships) in all of the models in Table 6 are positive and differ significantly from zero which implies a positive impact on a firm's ability to act centrally. Firm's partnering experience is therefore also an essential determinant for its centrality–based network capability. In sum, all three hypotheses are largely supported by the instrumental variable panel models and the results clearly indicate that a firm's efficiency, its dependency on its complementary resources and its experience at managing its partnerships are relevant determinative factors for a firm's centrality–based partnering capability.

4.4 Discussion

Firms that are centrally positioned within a network can better control and exploit worthwhile opportunities for obtaining information through links to other firms, and in turn gain competitive advantages in the marketplace. This central position of a firm plays an especially important role in the high technology industry with substantial innovation and knowledge transfer between different sectors. From a managerial perspective, positioning the firm centrally requires capable managers to improve their information efficiency and their skills to choose suitable partners. The results of the present study suggest that it is beneficial for managers to get access to information through a number of diverse contacts, avoiding duplicating contacts which leads to inefficient networks. Besides, the manager may also keep in mind that a partner may

[12] Hierarchy measure is negatively related to firm's dependency on its complementary resources as discussed in Section 4.2.2.

either unpredictably free–ride by limiting its dedication in an inter–firm cooperation or simply adopt opportunistic behaviours, which could cause informational hurdles in the cooperation network (Gulati, 1995). Thus, a good access to market information is essential to find an appropriate partner. Firms can learn about potential partner's capability and reliability from many sources, one of which is their network of prior collaborators, which enhances trust both by providing information about each other's reliability and by reinforcing a concern for reputation. Apart from selecting linkages based on past partners, managers could also choose to build up network resources by seeking out partnerships with central firms (Gulati, 1999), since connecting to well–positioned companies with a high network status is more valuable for the knowledge and information transfer than just being connected to others in a network of whatever positioned (Hagedooen and Duysters, 2002). Another network strategy that a manager could adopt is to anticipate their network participations and strategically initiate selective network contacts. Inter–firm networks serve as strategic resources that managers can proactively design for future choices and develop over time to meet their objectives (Walter *et al.*, 2007). Therefore, in order to better organize the cooperative relationships and thus attain a central position in a high–tech network environment, the managers can take a forward–looking view on the desired network structure of partners in the future and work backward on their current network strategy (Gulati, 1999).

Choosing appropriate R&D partnerships is a crucial step for practicing managers in an innovative high technology industry, since it can affect the success of a firm's innovation strategies and the effectiveness of a firm's R&D capabilities. Obviously, R&D partnerships are important external sources of a firm, through which it can access knowledge and innovation generated outside its technological cluster. However, firms can only identify and acquire relevant external knowledge through internal R&D activities, especially internal learning capacities, since they determine the extent to which a firm can assimilate and exploit new knowledge from other firms. This is also called absorptive capacity, which was defined by Cohen and Levinthal (1990). Investing in such absorptive capacity allows a firm to effectively exploit external information for its own use. Nicholls–Nixon (1993) investigated the effects of absorptive capacity in pharmaceutical companies' responses to the technological discontinuity brought by newly founded biotechnology firms, and found out that firms with high levels of absorptive capacity invested more in their own R&D and managed

communications more effectively with their cooperation partners. Thus, internal capabilities and external collaboration are complementary but not substitutes for one another, which means that firms need both capacities to develop their innovation strategy successfully (Powell and Brantley, 1992; Powell *et al.*, 1996). From a managerial perspective, balancing an internal innovation strategy with an external R&D partnering strategy is an important strategic decision for firms' innovativeness (Roijakkers, 2003; Vanhees, 2006). In a high degree of technological uncertainty that surrounds industrial development, firms that manage to have a high level of internal capability and external R&D partnering, would be capable to obtain competitive advantage and superior financial performance in the high–tech research network (Santos, 2003).

In particular, from a managerial perspective on the pharmaceutical biotechnology research networks, these large pharmaceutical companies should develop their research capability by using a variety of R&D partnerships with small biotechnology, but they should avoid time–consuming and costly partnering activities with companies that are not operating at the forefront of knowledge seeking and technology development (Hagendoorn *et al.*, 2006). Small biotechnology firms should operate their business with rather different strategies due to their weak positions in the high–tech market in comparison to large pharmaceutical companies. It is highly possible that once the large pharmaceutical companies have absorbed critical knowledge from the smaller biotechnology firms, they would discontinue their partnerships with these small partners (Roijakkers *et al.*, 2005). Thus, to survive in the fiercely competitive high–tech industry, biotechnology firms not only need to develop up–to–date technological knowledge and build up linkages to large pharmaceutical companies for funding their launching projects, but also need to develop long–term network strategy in terms of avoiding over–dependence on a few large pharmaceutical companies.

5 Conclusions

Economics provides insights into the inter–firm R&D network in the sense that the combined value of the resources resulting from a firm's cooperation exceeds the sum of resources coming from their separated economic activities. From the view of theoretical

network formation, a firm's incentive to form parwise links results from its reciprocal interests and maximizing a firm's incentive in partnerships may lead to a tension between individual incentive and social welfare. In most cases, R&D collaborations appear to generate positive effects on the societal welfare, so government policies generally encourage technological cooperation between high technology firms. In a high–tech environment with rapidly developing knowledge and innovation, research cooperations are an essential strategy for firms to become more successful. As a result, the R&D cooperation network in the pharmaceutical biotechnology industry has experienced a significant evolutional change in its size and structure during 1991–1998.

Not only network structure, but also a firm's strategic position in the network influences the proceeds from the inter–firm R&D cooperation. Central firms obtain information much more easily and rapidly and hence occupy advantageous structural positions in a research network, while peripheral firms hardly gain any benefits from participating in the cooperation. There are three structural properties to the actor centrality as summarized by Wasserman and Faust (1994): degree, closeness, and betweenness. Degree centrality takes only direct neighbours of an actor into account and if the indirect contacts need to be considered, we look upon closeness centrality, which measures the distance from one actor to all other actors in the network. The closeness centrality of an actor increases when the total distance to all other actors decreases. The importance of an actor for the circulation of information is captured by the concept of betweenness centrality. An actor with higher score of betweenness is more likely to be a link in more information chains between other actors and thereby has an important role as an intermediary in the communication network. Based on these measures, a list of the most important firms in the time period 1991–1998 was compiled. More than half of these firms are pharmaceutical companies, indicating that pharmaceutical companies may play a more dominant role than biotechnology firms in the 1990s. From the descriptive analysis (Table 4 in Section 3) and graphical illustration (Figure 4 in Section 3), it becomes evident that pharmaceutical companies have indeed developed into dominant star players with multiple partnerships while holding central roles in the R&D network during the 1990s.

Apart from evaluating the network on the individual level, this paper also provides the conceptions of network–level centralization and examines the research cooperation on the level of the entire network. Three distinct structural properties (degree, closeness and betweenness) that have been defined as bases for developing measures of

actor–level centrality were also used to construct indices of network–level centralization. The results from the descriptive analysis show that both degree–based and betweenness–based network centralization are not high in the time period 1991–1998, which implies that the distribution of overall positional advantages in the pharmaceutical biotechnology industry is, to a large degree, not unequal and even though most firms in this sector are linked to the R&D network, some of them are more active than others.

In the empirical part (Section 4), we applied panel data to determine the factors that could influence firm's centrality–based partnering capability in pharmaceutical biotechnology by using the network theory of "structural hole" and statistical methods of 2SLS and optimal GMM. Our results suggest that firm's efficiency, firm's dependency on its complementary resources and firm's experiences at managing partnerships are important determinants for firm's centrality–based partnering capability. Our findings also have implications for the practicing managers in the high technology industry. For instance, if managers want to keep the company in the inter–firm partnerships with valuable contacts, it is necessary for them to improve their partner selecting skills. Practicing managers can meet their objectives by implementing different network strategies, such as selecting linkages based on past partners, seeking out partnerships with central firms, or proactively designing their future partner choices. Furthermore, in order to obtain competitive advantage and superior financial performance in the high–tech R&D network, balancing internal innovation strategies with external R&D partnering strategies is also crucial for practicing managers. Specifically, in the pharmaceutical biotechnology sector, the large pharmaceutical companies need to be selective in choosing partners and avoid time–wasting cooperations with partners who are technologically outdated, while small biotechnology firms need to keep pace with rapidly changing innovative developments and meanwhile avoid over–dependence on a few large pharmaceutical partners.

Our study not only has empirical and managerial implications for understanding the firm's strategic partnering behaviour, it also has some theoretical implications. The results from the empirical analysis potentially points out the relation between the centrality measure and the conceptions in the network theory of "structural hole", which implies that the network theory can be used as an instrument to improve our understanding of a firm's strategic behaviour in establishing its partnerships. In this context, management literature on inter–firm networks can be inspired from the

conceptual ideas of network theory to improve the understanding of relevant issues, such as how managers could effectively create and design networks comprising various forms of partnerships (Hagedoorn *et al.*, 2006).

In addition, there are a number of options for further studies. In the current paper, the determinative factors for firm's centrality–based network capability are only empirically tested in the pharmaceutical biotechnology sector. Further research can reveal whether the same determinants we found are also important elements for firm's centrality–based partnering capability in other high technology sectors. Considering a broader set of factors that may influence a firm's ability to position itself centrally and a larger size of sample firms will also further deepen our understanding of the complex mechanisms in inter–firm R&D networks.

Appendix: Tables

Table 1: Normalized degree–based network descriptive statistics in pharmaceutical biotechnology during 1991–1998

Year	Mean Degree	S.D. Degree	Min.	Max.	Network centralization
1991	1.21	0.66	0.93	5.56	4.43%
1992	0.94	0.56	0.62	3.09	2.17%
1993	0.83	0.60	0.51	4.62	3.82%
1994	0.75	0.62	0.40	3.97	3.24%
1995	0.65	0.58	0.31	4.01	3.38%
1996	0.64	0.63	0.27	4.56	3.94%
1997	0.60	0.67	0.22	5.22	4.63%
1998	0.54	0.54	0.22	3.44	2.91%

Source: Recombinant Capital.

Table 2: Normalized closeness–based network descriptive statistics in pharmaceutical biotechnology during 1991–1998

Year	Mean Closeness	S. D. Closeness	Min.	Max.
1991	0.03	0.01	0.02	0.07
1992	0.03	0.01	0.01	0.06
1993	0.03	0.03	0.01	0.11
1994	0.07	0.05	0.01	0.17
1995	0.12	0.06	0.01	0.25
1996	0.15	0.07	0.01	0.27
1997	0.18	0.07	0	0.31
1998	0.15	0.07	0	0.27

Source: Recombinant Capital.

Table 3: Normalized betweenness–based network descriptive statistics in pharmaceutical biotechnology during 1991–1998

Year	Mean Betweenness	S. D. Betweenness	Min.	Max.	Network Centralization
1991	0.02	0.06	0	0.43	0.42%
1992	0.09	0.23	0	1.09	1.01%
1993	0.24	0.70	0	4.51	4.30%
1994	1.26	3.29	0	21.03	19.84%
1995	1.15	2.61	0	25.44	24.37%
1996	0.88	1.78	0	11.62	10.77%
1997	0.67	1.49	0	11.07	10.42%
1998	0.64	1.38	0	11.78	11.17%

Source: Recombinant Capital.

Table 4: The 40 most important players in pharmaceutical biotechnology in 1991–1998[13]

	Company	Sector	Normalized Degree	Normalized Closeness	Normalized Betweenness
1.	Abgenix	biotech	1.29	0.24	3.55
2.	Acacia Biosciences	pharmaceutics	0.86	0.22	3.19
3.	Affymetrix	biotech	3.44	0.25	7.81
4.	American Home Products	pharmaceutics	1.72	0.23	2.90
5.	Amersham Pharmacia Biotech	bio–pharmaceutics	1.72	0.24	3.52
6.	Bayer	pharmaceutics	2.80	0.26	7.38
7.	Bristol–Myers Squibb	pharmaceutics	3.01	0.23	5.41
8.	Centocor	pharmaceutics	1.29	0.24	3.14
9.	Chiron	biotech	1.72	0.23	3.02
10.	Corixa	bio–pharmaceutics	1.51	0.22	1.37
11.	Du Pont	pharmaceutics	1.08	0.21	2.97
12.	Elan	biotech	2.15	0.23	3.73
13.	Eli Lily	pharmaceutics	2.80	0.24	5.21
14.	Gene Logic	biotech	1.29	0.23	2.59
15.	Genentech	biotech	1.51	0.22	2.95
16.	Genetics Institute	biotech	1.08	0.23	2.03
17.	Genome Therapeutics	biotech	1.94	0.24	5.06
18.	Genzyme	biotech	1.72	0.23	3.33
19.	Genzyme Transgenics	biotech	1.08	0.21	2.24
20.	Hoechst Marion Roussel	pharmaceutics	1.72	0.23	4.11
21.	Immunex	biotech	1.08	0.22	2.02
22.	Incyte Pharmaceuticals	pharmaceutics	2.58	0.27	8.84
23.	Lexicon Genetics	pharmaceutics	0.86	0.22	1.20
24.	Medlmmune	pharmaceutics	1.08	0.22	2.25
25.	Merck	pharmaceutics	1.51	0.23	3.40
26.	Millennium Pharmaceuticals	bio–pharmaceutics	1.51	0.22	3.06
27.	Novartis	pharmaceutics	2.37	0.24	5.99
28.	Novo Nordisk	pharmaceutics	2.15	0.24	3.66
29.	OncorMed	biotech	1.29	0.24	4.03
30.	Oxford Asymmetry	pharmaceutics	1.94	0.23	3.25
31.	Oxford GlycoSciences	biotech	1.29	0.22	1.44
32.	Pasteur Merieux Connaught	biotech	1.51	0.21	2.67
33.	Peptide Therapeutics	biotech	1.08	0.22	2.31
34.	Pfizer	pharmaceutics	3.44	0.25	6.59
35.	Pharmacia & Upjohn	pharmaceutics	1.94	0.23	4.94
36.	Roche	bio–pharmaceutics	2.37	0.23	4.94
37.	**Schering Plough**	**pharmaceutics**	**3.44**	**0.28**	**11.78**
38.	SmithKline Beecham	pharmaceutics	3.44	0.25	8.76
39.	Tripos	pharmaceutics	1.51	0.22	2.81
40.	Zeneca	pharmaceutics	1.72	0.24	3.44

Source: Recombinant Capital.

[13] The names of companies are listed alphabetically.

Table 5: Descriptive statistics and correlations

	Variable	Mean	S. D.	1	2	3	4	5	6	7
1.	Centrality–based partnering capability	0.8859	0.9287	–						
2.	Efficiency level	0.8948	0.2710	0.2989	–					
3.	Dependency	0.0824	0.2625	–0.2694	0.1130	–				
4.	Partnering experiences	1.5546	1.1145	0.8449	0.4154	–0.3194	–			
5.	Duration	3.9000	2.0778	0.4864	0.5203	–0.1641	0.5855	–		
6.	Time effect (1996)	0.2500	0.4344	–0.0109	–0.0639	0.1578	–0.0695	–0.0767	–	
7.	Time effect (1997)	0.2500	0.4344	–0.1434	0.1223	–0.1020	0.0733	0.0906	–0.3333	–
8.	Time effect (1998)	0.2500	0.4344	0.2419	0.1525	–0.1553	0.1504	0.2439	–0.3333	–0.3333

Table 6: Panel instrumental variable estimates

	2SLS		**2SLS with Robust Standard Errors**		**Optimal GMM**		
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Efficiency level	2.3103*	2.2569*	2.3103*	2.2569*	1.9365*	1.7569	2.2706*
	(1.2421)	(1.2140)	(1.2140)	(1.2306)	(1.0886)	(1.1431)	(1.2725)
Dependency	-0.7216*	-0.6955*	-0.7216*	-0.6955*	-0.6523*	-0.5733*	-0.7171**
	(0.4340)	(0.4062)	(0.3923)	(0.3604)	(0.3742)	(0.3473)	(0.3612)
Partnering experiences	0.5650***	0.5690***	0.5650***	0.5690***	0.5908***	0.6068***	0.5707***
	(0.1017)	(0.0990)	(0.0953)	(0.0937)	(0.0906)	(0.0900)	(0.0921)
Duration	-0.1171*	-0.1179	-0.1171*	-0.1179*	-0.1106*	-0.1043*	-0.1302**
	(0.0693)	(0.0720)	(0.0598)	(0.0648)	(0.0567)	(0.0618)	(0.0647)
Time effect(1996)	-0.0328		-0.0328		-0.0443		
	(0.1598)		(0.1951)		(0.1912)		
Time effect(1997)	-0.6165***	-0.5776***	-0.6165***	-0.5776***	-0.6684***	-0.6077***	-0.6213***
	(0.1997)	(0.1462)	(0.2101)	(0.1335)	(0.1923)	(0.1239)	(0.1311)
Time effect(1998)	-0.0681		-0.0681		-0.0778		
	(0.1934)		(0.1893)		(0.1834)		
Constant	-1.3639**	-1.3564**	-1.3639*	-1.3564*	-1.0650*	-1.0156	-1.3077*
	(0.6794)	(0.6838)	(0.7087)	(0.7445)	(0.6103)	(0.6674)	(0.7756)
Instrument:							
Clustering coefficient	√	√	√	√	√	√	
Biotechnology	√	√	√	√	√	√	√
US	√	√	√	√	√	√	√
Germany	√	√	√	√	√	√	√
Denmark	√	√	√	√	√	√	
Firm age	√	√	√	√	√	√	√
p-val in overidentification test	0.5442	0.5241	0.1858	0.1774	0.1858	0.1774	0.2569
p-val in endogeneity test	0.0015	0.0020	0.0020	0.0029	0.0020	0.0029	0.0021
Number of observations	160	160	160	160	160	160	160
Centered R-squared	0.4266	0.4402	0.4266	0.4402	0.5166	0.5566	0.4355
Uncentered R-squared	0.7007	0.7078	0.7007	0.7078	0.7477	0.7685	0.7053

Notes: Standard errors in parentheses; significance–levels * p<0.1; ** p<0.05; *** p<0.01.

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