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Formation of Industrial Research Networks

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CHAPTER 1

Introduction

Rapid technological advance has created an enormous variety of technologies, and industrial production has strongly benefited from its increasingly diverse technological basis. This ongoing trend has given rise to the "multi-technology firm" which handles diverse technologies in order to manage and to develop its product lines (see Granstrand, 1998; Powell et al., 1996, for example). The richness and complexity of the increasing knowledge base eventually creates an impediment to a firm's growth because its internal knowledge base may become insufficient for innovation. Yet firms need to innovate in order to stay competitive in their markets. Therefore, firms need to employ complementary knowledge residing outside the boundaries of the firm.

Alliances are frequently used to address this issue nowadays. In strategic alliances, two or more firms join, exchange or share their resources in order to strengthen their resource base or to develop a joint business. Firms form strategic alliances to target any activity along the value chain, from research to production to marketing and distribution. Research alliances are especially frequent in high-tech industries, where firms connect for technology transfer, sharing and joint undertaking of research. Although motives to form research alliances vary, access to complementary knowledge is the most important factor according to the industry actors (Hagedoorn, 1993; Herrling, 1998).[1] Alliances serve this purpose well because inter-firm cooperation can

[1] Motives for research alliances may stem from efficiency considerations or firm interdependencies (see Hemphill and Vonortas, 2003). Efficiency is enhanced, for example, due to realization of economies of scale and scope, easier access to finance, or using of extant capacities. In high-tech industries however, where we observe especially many research alliances, access to complementary knowledge, a form of firm interdependence, seems to be the most important driver of alliance formation (Hagedoorn, 1993; Herrling, 1998).

be extremely effective to transfer tacit knowledge. Therefore, the broadening of the knowledge base induces interaction among the actors which is governed by alliances. This argument may well explain the rapid rise in research alliances starting in the mid 1970s.

The increasing importance of interaction among actors is reflected in theoretical approaches to innovation. In the 1980s, a first step has been the "chain-linked model" of Kline and Rosenberg (1986), which is a general product-life cycle model. Originally this model was proposed as a reaction on the "linear model" of innovation. The "linear model" reflects the thinking that a new product passes four subsequent stages. In the first stage, basic research opens the opportunity for a certain technological application. A corresponding product is developed in the second stage. In the third and fourth stage the product is produced and marketed. The "chain-linked model" superseded the conception of innovation as a linear process within the isolated firm. It extends the "linear model" mainly by noting two things. Firstly, innovation activities of the different stages are heavily interconnected by forward and backward links. Secondly, the model incorporates a knowledge pool outside the boundaries of the firm which is potentially relevant in all innovation activities. Thus, the "chain-linked model" points to the relevance of interaction for innovation, within the firm as well as across firm boundaries.

During the last two decades the "systems of innovation approach" has emerged which further emphasizes interaction for innovation (see for example Edquist, 2005). The systems approach to innovation argues that the innovation performance of nation states, regions or sectors depends not only on the performance of the individual actors but also on how the actors interact with each other. The innovation process is depicted as a joint learning activity of firms and other actors, such as research institutions, which is governed by government agencies and financial institutions. Thus, innovation is conceptualized as an interactive process of creation, use and diffusion of economically useful knowledge.[2] Within the innovation approach, learning through interaction among heterogeneous actors is key to innovation. This puts the networks formed by the actors at the fore.

The structure of the research network is likely to affect the way knowledge is created and diffused. Empirical studies suggest that the position a firm takes in the research network affects its knowledge sourcing and production behavior. For example firms which are more central in the network and firms within a well connected group might have a higher research productivity (Ahuja, 2000). Because joint research always entails knowledge sharing and spillovers, the structure of the network is also likely to affect diffusion and accumulation of technological knowledge within the system (Cowan

[2]The literature provides varies definitions and classifications of knowledge (see Arora et al., 2002; Cowan et al., 2000; Rosenberg, 1983). This thesis focuses on technological knowledge without employing a strict definition. Following Arora et al. (2002), we assume that technological knowledge is economically useful and may stem for example from science, engineering or practicing.

and Jonard, 2004).

In this light, a crucial question becomes how networks actually are formed. This thesis considers how the technological and social endowment of firms affect their decisions to form bilateral alliances, and investigates to what extent our knowledge on the formation of bilateral alliances helps to explain the structure of the alliance network. A theoretical model yields insights into how the technological endowment of firms may affect both the global network structure and the position of firms in the network. An empirical analysis estimates technological and social network effects on alliance formation. The estimated model is shown to be rather informative with respect to the firm's position in the network but not very informative with respect to the global network structure.

Prior approaches

Game-theoretic approaches to network formation started off with the connections model of Jackson and Wolinsky (1996). In the connections model, identical agents maximize profits by forming links with each other. Formation of links is costly and profits arise through direct links as well as indirect links. The connections model led to many descendants with variations of this setting (see Jackson et al., 2003, for a review). Typically, the analysis focuses on efficiency and stability of the network. A network is stable if no agent has an incentive to deviate from the given network by creating a link or dissolving a link. In general it is found that stable networks are not necessarily efficient. But models in this type of setting are difficult to solve. Because agents benefit from indirect links, the linking decision of an agent becomes contingent on the overall network structure. Therefore, for larger networks, a full characterization of all stable structures usually is not feasible. In cases where a full characterization is feasible, stable networks are not especially realistic: the empty network, the complete network, or the star. A further commonality to all these models is that agents are identical, having essentially no properties. The only characteristic of an agent is its position in the network. The model of Goyal and Moraga-Gonzalez (2001) and Goyal and Joshi (2003) are rare exceptions in that cooperation between two agents affects their production costs in a subsequent competition stage. However, also in this model agents are initially identical and, hence, have no identity.

Only recently have theoretical models introduced initial properties to the nodes in order to allow for more realistic network structures. Examples are the islands model of Jackson and Rogers (2005), a spatial version of the connections model by Carayol and Roux (2009), or the knowledge portfolio model by Cowan et al. (2007). In these models the properties of nodes affect the attractiveness of particular nodes as partners. In the island model agents are positioned on various islands. Link formation is less costly for agents which are on the same island and more costly across islands. Thus, agents on the same island are more likely to form a link and the network becomes clustered.

In the model of Carayol and Roux (2009), as in the connections model, agents profit from direct and indirect links and have costs. The difference is that agents are located in space and costs are a function of the agents' geographic distance.[3] A stochastic process of network formation results, for certain parameter ranges, in real-world like networks having the small world properties, i.e. sparse with short average path length and high clustering. In the knowledge portfolio model of Cowan et al. (2007) agents are endowed with a knowledge vector which is a vector of integers. In order to innovate, agents search for complementary knowledge and combine their knowledge vectors. Also this model generates real-world like networks and moreover shows that the network structure depends on the modularity of the innovation tasks.[4] In all three models, the properties of the nodes affect the attractiveness of particular agents as partners. This, of course, implies that the relative properties of the agents predict which links are likely to be formed and the structure of the network may reflect the structure of some underlying space in which agents are located.

How relative properties of the firms affect link formation has recently become a central issue in empirical alliance studies.[5] Empirical studies of alliance formation estimate the factors which cause two particular firms to form an alliance. The main interest, therefore, is in how firms are technologically, economically and/or socially related to each other. Summarizing this literature, it is important to distinguish studies on the formation of research alliances from studies on the formation of alliances per se which may include various types of alliances. First, the literature on alliance formation is large whereas only a few studies consider formation of research alliances. Second, and more important, the two streams follow different approaches. Studies of research alliances focus on the need to combine complementary knowledge. The larger literature on alliance formation is primarily occupied with social relations of the firms. In the language of Eisenhardt and Schoonhoven (1996), research on research alliances is largely concerned with the inducement of alliance formation, whereas research on alliances per se largely focuses on the opportunity of alliance formation.

Interest in the social environment of the firm in economics has been spurred by structural sociology. This approach builds on the conviction that the individual is "purposeful and goal directed, guided by interests [...] and by the rewards and constraints imposed by the social environment." (Coleman, 1986, p.1310). The claim that economic action is the result of inducements and opportunities is not a novelty

[3] The model of Carayol and Roux (2009) resembles another spatial version of the connections model, the model of Gilles and Johnson (2000). One difference is that agents are located on a ring in the former and on a line in the latter model. A second difference is that Carayol and Roux (2009) consider more actors within a stochastic process of network formation and are concerned with the generation of real-world like networks. Gilles and Johnson (2000) analyze the relationship between efficiency and stability for a smaller set of actors.

[4] The issue of modularity is addressed in chapter 5.

[5] Previously, the literature on alliances has been mainly concerned with other issues such as the governance of alliances or motives of alliance formation.

coming from this approach but has been shared by many early economists such as Smith, Locke or Mill (see Coleman, 1986, p.1310). The novelty rather stems from the conceptualization of the social environment. The social environment is thought to be realized through existing social relations among individuals. Therefore, the structure of the social network defines the (local) working of social norms, and, each individual acts within its own local social environment (Granovetter, 1985).

Acknowledging that firms act within a historical and social context helped to explain observed economic behavior which seems inconsistent with the "traditional" perspective of the rational, self-interested and isolated economic actor. For example research on alliances needed to explain how it may be that two firms invest in relation-specific capital and exchange of knowledge under incomplete contracts. Within the "traditional" view there are serious impediments for alliance formation. Because two firms are separate legal entities with diverging interests, they might encounter appropriability problems (e.g. leakage of knowledge) and moral hazards (e.g. opportunistic behavior) (Williamson, 1991). Furthermore, incomplete information on potential partners hinders partner search, and ongoing coordination efforts are necessary during the alliance in order to be successful. All these issues are better understood when the social environment of the firm is taken into account. Social and business relationships provide (trustful) information and sustain norms of behavior (Gulati, 1998).

Empirical research on alliance formation has focused on social effects from the network of prior alliances (Gulati and Gargiulo, 1999; Powell et al., 2005, are probably the most prominent). The argument for doing so is that, although the network of prior alliances does not represent the complete social environment, it still is an important part of it. The typical approach is to construct the network of prior alliances among a sampled set of actors, then measure firm-pair specific network statistics on the network and finally introduce these statistics as independent variables in a regression where the dependent variable is whether or not a certain alliance forms. Empirical results suggest for example that trust, reputation and the connectedness of the actors are influential for alliance formation (Gulati and Gargiulo, 1999). Although this literature widely acknowledges the importance of inducements and opportunities, inducive factors are typically treated as factors which need to be controled for but which are not of special interest. Therefore, strategic inducements for alliance formation are captured by rough proxies such as industry affiliation, type of organization (public, private, non-profit) or firm size (Gulati and Gargiulo, 1999; Powell et al., 2005; Rosenkopf and Padula, 2008). An issue in this literature is that the social capital of the firm is a derivative from and proxied by the network structure. For example, trust among firms is said to arise out of repeated alliances and is measured by the number of prior alliances. This approach faces the risk of spurious path dependency because exogenous factors as well might cause stable network structure. If incentives to form alliances are caused by exogenous factors which remain stable over time, then the network structure is likely to remain stable as well.

Empirical studies on the formation of *research* alliances are mainly concerned with how technological endowment of two firms affect their decision to form an alliance. For this endeavor one first needs an idea which technological combinations are economically useful. Most studies which investigated this question took the standpoint that alliance benefit depends on the relatedness of the knowledge of the firms (see e.g. Cantwell and Colombo, 2000; Mowery et al., 1998; Rothaermel and Boeker, 2008). On the one hand, firms ally to access complementary knowledge and, therefore, the knowledge bases of the partnering firms need to be different to some extent. Another way to put this argument is that new knowledge is generated by recombination of prior knowledge, and, novel combinations are possible to the extent that the knowledge bases of the firms are different. On the other hand, knowledge bases need to be similar because absorptive capacity of the firms needs to be sufficiently high to evaluate each other's knowledge and to commercially exploit the results of the cooperation (Cohen and Levinthal, 1990). Hence, the knowledge bases of the partners should neither be too different nor too similar. The knowledge base of the firm is typically measured using the patent portfolio of the firm. Then, knowledge relatedness is conceptualized as the proximity of two patent portfolios, where proximity is indicated for example as overlap of patent citations or similarity of patenting frequency in technological fields. The results of these studies mostly agree that technological proximity is influential for alliance formation. Depending on the industry, alliance form (joint venture, research agreement), and distance measure, studies find that firms are most likely to form alliances when they have an intermediate or small technological distance (Mowery et al., 1998; Cantwell and Colombo, 2000, respectively). The issue that the prior network of alliances might provide private information or trust is widely neglected in these studies.

The alliance may be considered as the elementary unit in the process of network formation. A network usually is described by the set of actors and the links between the actors. The adjacency matrix contains all this information. The adjacency matrix is a binary matrix with the number of rows and columns equal to the number of actors. A cell in the adjacency matrix is set to one if an alliance exists between two respective actors and zero else.[6] All higher-level network structures can be extracted from the adjacency matrix. The number of alliances of the firm corresponds to the row and column sums. The alliance portfolio of the firm is fully described by the row and column vectors. The ego-network of the firm entails merely the set of partners and the links among them. All these levels have been subject to empirical research, with respect to both alliances and research alliances.

Probably most often investigated is the number of alliances of the firm, be it re-

[6] This holds for "simple" networks, with only one type of link either existing or not and a fixed set of actors which formed alliances over a certain time. Different types of links might be represented by several matrices, valued links by numerical entries in the cells, and time evolution by stacking adjacency matrices over several time periods.

search alliances or other types of alliances (Ahuja, 2000; Powell et al., 1996; Shan et al., 1994; Walker et al., 1997; Zhang et al., 2007). Consistent with the results on alliance formation, it has been found that firms with high social capital or high technological capital have many alliances.[7] Furthermore, connectedness within the local social neighborhood and the breadth of the firm's knowledge base has been found to positively affect the number of alliances of the firm (Walker et al., 1997; Zhang et al., 2007, respectively). One observation (which is addressed in chapters 3 and 4) is that, although all the network levels (alliance, firm ego-network, etc.) are naturally connected, empirical studies usually remain at one level of analysis. A notable exception is the study of Stuart (1998) who investigates how the technological endowment of firms affect alliance formation as well as the number of alliances of the firm. Therefore an interesting question is to what extent studies at different levels are informationally equivalent. For example, does an empirical study of alliance formation provide good information on how the network structure forms?

Thesis structure

This thesis investigates the formation of industrial research networks. The focus is on how heterogeneous technological capabilities of firms affect their decision to form alliances and, thereby, shape the structure of the network. The technological explanation of network formation is complemented by taking into account social structure effects arising from the prior network of alliances. In doing so, the thesis mainly builds on the literature on alliance formation, the resource based view of the firm and social network theory and analysis.

Chapter 2 introduces technological distance between firm-pairs as a cause of network formation in a theoretical model. The theory on absorptive capacity, developed by Cohen and Levinthal (1990), implies that benefits of joint knowledge creation by two actors vary with their cognitive distance. In an empirical application, Mowery et al. (1998) found an inverted-U effect of technological distance on the formation of joint ventures. Chapter 2 investigates how that technological distance effect between firm-pairs contributes to the structure of the alliance network among multiple actors. In the model, firms are positioned in technological space and two firms form an alliance if their technological distance is within a profitable range. The implication of the model is that when the profitable range is small (large) relative to the technological space,

[7] A question also investigated by Eisenhardt and Schoonhoven (1996). This study is exceptional in several regards. First, similar to Ahuja (2000), Eisenhardt and Schoonhoven (1996) investigate jointly social and technological factors of alliance formation. Second, social embeddedness is not measured on the prior network of alliances but proxied by the career history of the top management team. Third, the study does not investigate technological competence by the firm's patent portfolio but the firm's technology strategy by questionnaires and product features. By doing so, the study circumvents the issue of network endogeneity and includes explicitly the technology strategy of the firm.

firms closer to the center of technological space are more (less) central in network space.

Chapter 3 investigates the empirical relevance of the theoretical model for a research network of the pharmaceutical industry. Important methodological steps are the development of the testing strategy, the measurement of technological distance and the transfer of the random and fixed effects estimation approach for panel data to the estimation of firm-pair observations. The empirical results confirm that technological distance affects pairwise alliance formation which, in turn, influences higher-level network structures, especially the firm ego-network.

Chapter 4 compares technological distance to social network variables as explanations of network formation. The social network literature argues that alliance formation is contingent on a concrete social system which is built through business and personal relationships (Granovetter, 1985). Taking the network of prior alliances as proxy for the overall social network, empirical studies have found significant social-network effects but tend to ignore inducements for alliance formation (e.g. Gulati and Gargiulo, 1999). This chapter presents joint estimates of the standard social network effects and the technological-distance effect on alliance formation. Social and technological effects are found to be similarly strong in size and significance. The sensitivity analysis, however, shows that social-network effects can be expected to have an upward bias due to spurious path dependency. This affects the interpretation of own estimations but also of previous findings in the empirical literature.

Chapter 5 investigates the effect of modularity in research activity on the alliance network in an empirical application to the vaccine industry. The idea that product modularity might induce organizational modularity and vice versa is at the origin of many theoretical and empirical contributions (e.g. Brusoni et al., 2001; Baldwin, 2008). Most of these studies are concerned with engineering design. This chapter considers vaccines as nearly modular products. The analysis suggests that especially integrated pharmaceutical firms with a large vaccine portfolio benefit from the modular product architecture. Furthermore, the study suggests that the technological specialization of biotechnology firms does not predetermine the strategy of the firm. Financial and organizational resources might be more constraining.

Chapter 6 integrates the findings of the thesis and concludes.

CHAPTER 2

Theoretical Model of Network Formation

2.1 Introduction

Joint research and development (R&D) by two or more firms is frequent when firms face high innovation pressure and technological knowledge is dispersed among firms (Powell et al., 1996). Under these conditions the R&D alliance is important to generate technical innovations, because it governs the process of recombination of existing knowledge residing in different firms.[1]

The choice of an alliance partner involves a trade-off. On the one hand, alliance partners need the absorptive capacity to evaluate each others knowledge and to appropriate the results of the alliance (Cohen and Levinthal, 1990). The more similar the knowledge of the alliance partners, the higher their absorptive capacity. On the other hand, firms ally to access new knowledge and form novel combinations (Nooteboom et al., 2007). The more dissimilar the knowledge of the alliance partners, the higher the novelty gain. For a beneficial alliance, absorptive capacity and novelty gain are both preferred to be high. However, with increasing cognitive distance absorptive capacity decreases and novelty gain increases. This implies that benefit is maximized at some medium cognitive distance, the point of optimal cognitive distance (Nooteboom et al., 2007). The empirical literature attests to the relevance of the inverse-U-shaped benefit-distance effect. Joint R&D is most likely for pairs of firms having intermediate technological distances (Mowery et al., 1998; Nooteboom et al., 2007).

Observing that the fundamental building block of a network is the bilateral alliance, the previous results invite the question whether the technological distance effect is vis-

[1]See (McGee, 1995) for an historical account of technological novelty by recombination.

ible in aggregate network structures. Could the distribution of firms over a knowledge space, combined with the technological distance effect, determine the structure of the network and the position of firms therein?

The structure of an R&D network is likely to influence the generation and diffusion of knowledge in an industry. Specifically, Cowan and Jonard (2004) argue that small world networks (i.e. highly clustered networks with small path length (Watts and Strogatz, 1998)) foster knowledge accumulation of an industry. At the firm level, empirical work shows that a firm's network position affects its knowledge sourcing and production behavior (Ahuja, 2000; Baum et al., 2000; Cockburn and Henderson, 1998; Gilsing et al., 2008; Powell et al., 1996; Shan et al., 1994). For example, a central position in the network gives a firm fast access to knowledge (Singh, 2005).

This chapter proposes a theoretical model to investigate the question how the distance-benefit effect between firm-pairs contributes to the network structure. We model profit-maximizing firms forming alliances. Profits are determined by the distance-benefit relationship. Whereas the distance-benefit relationship is common to all firm-pairs, each firm-pair has a specific technological distance. With the relationship and all distances given, we know the alliance decision of all firm-pairs and the network is completely determined. Thus, the network characteristics for the individual firm and the overall network can be derived. The intuition gained from the model is that the position of firms in the knowledge space in combination with the benefit-distance relationship affects the network structure and the position of firms therein.

The model follows the connections model of Jackson and Wolinsky (1996) and its extension, the spatial social network of Gilles and Johnson (2000). Our model set up can be seen as a specification of the latter in that it models the benefit distance relationship to be inverse-U-shaped. However, in contrast to the literature on connections models we do not focus on stability and efficiency (Jackson et al., 2003) but rather on the network characteristics implied by the model. This adds an economically motivated effect to the toolbox of network analysis, which has hitherto been dominated by socially motivated effects like referrals, trust or status (Powell et al., 2005).

The chapter is organized as follows: section 2 provides some further background on the literature. The model is introduced in section 3. The analysis in section 4 focuses on the firm network position resulting from the benefit-distance effect and the firm's position in technological space. Section 5 discusses central assumptions of the model. The final section concludes.

2.2 Background

Economic sociology and literature on knowledge generation and diffusion suggests that the structure of the network is crucial both for the development of firms and for the system as a whole. Yet it is not clear how the structure comes to existence. The important insight from economic sociology (Burt, 2001; Coleman, 1986; Granovetter, 1985) and organizational learning (Cohen and Levinthal, 1990; Kogut and Zander, 1992) is that alliances take place in a social and historical context (Hemphill and Vonortas, 2003). This leads to the argument that the prior social network guides the structure of the network of tomorrow because it mitigates appropriability problems, moral hazard as well as the coordination problem. Drawing from knowledge economics, this chapter proposes that the technological landscape also has a strong structuring element; an alternative which has been widely neglected in the previous literature.

For a beneficial alliance it is crucial that both partners are able to evaluate each other's knowledge and to use the new knowledge generated by the alliance. Cohen and Levinthal (1990) termed this ability the absorptive capacity of a firm. Evaluation of foreign knowledge and integration into one's own knowledge base is simpler when it is related to one's own prior knowledge. Therefore, driven by increasing absorptive capacity, we would expect the benefit of joint R&D to increase with as partners' knowledge bases become more similar. However joint knowledge creation is valuable exactly when partners contribute knowledge new to each other and combine it in a new way. In principle, the opportunity to form novel combinations is higher the more diverse are the knowledge bases of the partnering firms (Nooteboom et al., 2007). Hence, a higher cognitive distance between two firms yields a novelty gain. The discussion suggests a trade-off between absorptive capacity and novelty gain. For a beneficial alliance, both high absorptive capacity and high novelty are desirable. Since novelty responds positively and absorptive capacity negatively to an increase in cognitive distance, the expected benefit of an alliance is likely to be maximal at some medium cognitive distance (Nooteboom et al., 2007).

The concept of cognitive distance is very broad in that it incorporates any difference between the mind sets of the firms. Cognition includes not only the knowledge of facts but also e.g. interpretation, categorization and emotions. For R&D alliances technological knowledge seems most relevant and we may reduce the concept of cognitive distance to technological distance without losing too much insight. The implication remains the same: with increasing technological distance benefits of joint innovation first increase and then decrease. This has been tested empirically by (Mowery et al., 1998; Nooteboom et al., 2007), who found that joint R&D is most likely for pairs of firms having intermediate technological distances.

In this chapter, we propose a theoretical model of network formation which builds on this observation. We assume that there is an inverse-U-shaped benefit-distance effect and that alliance formation entails some fixed cost. Firms form an alliance whenever their technological distance implies a benefit which exceeds the cost.

This model is related to the knowledge portfolio model of Cowan and Jonard (2009) and the spatial social network model of Gilles and Johnson (2000). The knowledge portfolio model applies the idea of optimal technological distance for joint knowledge production in an evolutionary model. Firms are characterized by a binary knowledge vector. Two firms form an alliance when their knowledge vectors have sufficient overlap. During the alliance both firms learn and their knowledge vectors become more similar. In this way, past alliances indirectly affect future alliance formation. Cowan and Jonard (2009) show that in certain parameter ranges the optimal distance effect generates networks that mimic observed real-world networks, i.e. sparse, with high clustering coefficients and short average distances. The spatial social network model extends the communication model, in which agents profit from direct and indirect links (Jackson et al., 2003). In the spatial extension, the costs of tie formation depend on the social distance between two actors. Carayol and Roux (2009) showed that, similar to the knowledge portfolio model, the spatial social network model is capable of producing networks corresponding to the stylized facts of research networks.

We blend both models in that we build on the inverse-U-shaped distance benefit effect, as in (Cowan and Jonard, 2009). However, the set-up of the technological space is more similar to (Gilles and Johnson, 2000). This results in a simplification of both models as no indirect effects of link formation need to be considered: two firms decide solely on their technological distance, which is not altered by forming a research alliance. With this assumption, the model remains static. The advantage is that this simple set-up allows for analytical treatment and to shift the focus from the network structure to the firm network position. Furthermore, as the model remains with the main effect, a strong link to the empirical analysis in the following chapter is facilitated.

2.3 Model

Consider a population of firms located in a knowledge space with a well-defined distance metric, t. Firms form alliances for the purpose of joint innovation, so value resides not in firms but in alliances between firm-pairs. Assume that the benefit of an alliance depends on technological distance in the knowledge space but the cost of an alliance is fixed. For two firms, i and j, having distance t_{ij} in the knowledge (or technology) space, forming an alliance yields a benefit $f(t_{ij})$ and costs c. The alliance is valuable, and hence formed, if $f(t_{ij}) > c$.

The discussion of the technological distance effect implies that the value of an alliance is an inverse-U-shaped function of distance. In mathematical terms, $f(t)$ is defined to be a continuous, differentiable, real-valued, single-peaked function, with t being the technological distance between two firms. Assume further that there exists a finite t^* such that $\forall\, t \geq t^*$, $f(t) \leq 0$; and possibly there exists a t^{**} such that $\forall\, t \leq t^{**}$, $f(t) \leq 0$. Because the value function is single peaked and costs are assumed to be constant, all alliances in some range $[a, a + b]$ are profitable and hence realized. As depicted in figure 2.1, definitions of a and b follow from:

$$\begin{aligned} f(a) &= c \quad \text{with } a > 0, \\ \text{or} \quad a &= 0, \\ f(a+b) &= c \quad \text{with } b > 0. \end{aligned}$$

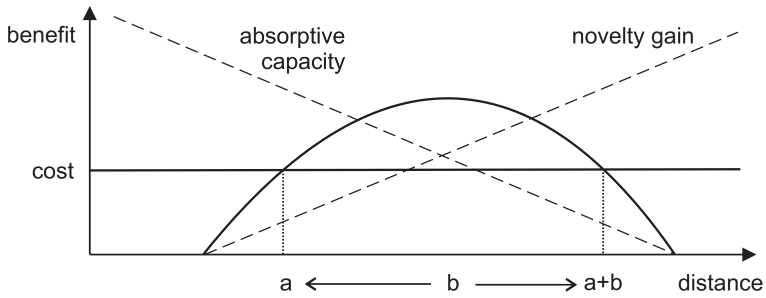

Figure 2.1: *The inverse-U-shaped benefit-distance relationship arises from the trade-off between absorptive capacity and novelty gain (the figure displays a multiplicative effect). Taking into account the costs of alliance formation, one finds the range $[a, a+b]$ in which alliances are profitable. (Adapted from Nooteboom et al., 2007.)*

By forming alliances the firms construct an alliance network. The network can be described as a graph, in which the firms are nodes and the alliances are the links connecting the nodes. Different assumptions about the nature of the knowledge space and the distribution of firms therein lead to different networks. This chapter examines a one-dimensional knowledge space, over which firms are uniformly distributed. This simplifies the analysis, but the intuition gained can easily be extended to multi-dimensional knowledge spaces with unevenly distributed firms. We treat two distinct knowledge spaces: an unbounded space — the real line; and a bounded space — the unit interval.

Unbounded space. In the first case, assume that the knowledge space is unbounded on the real line over which agents are uniformly distributed. In this case, the knowledge space is translation invariant, so agent 0, located at the origin, is a representative agent. This agent will maintain a link to an agent located at i if and only if $f(i) \geq c$. Thus an agent at the origin will form links to all agents located in $i \in [a, a+b] \bigcup [-a, -a-b]$, where a and b are defined as above.

In the unbounded knowledge space, all agents face the same problem. Now suppose the knowledge space is bounded between 0 and 1. Then agents in the center are in a different position than those at the boundaries because the boundaries restrict the set of potential partners.

Bounded space. How the boundaries restrict the neighborhood of firms can be seen in Figure 2.2. Consider for example the lower left graph. Consider links to the right of the agent. For the agent at $i = 0$, its neighborhood will run from a to $a + b$. As we increase i, the right neighborhood remains unrestricted until $i + a + b > 1$, or equivalently, $i > 1 - a - b$. As we increase i further, the right boundary restricts the neighborhood of agent i to be $[i + a, 1]$. Finally, at the point $i = 1 - a$, agent i no longer has any neighbors to the right. The partnering problem is symmetric to left and right, the same effect moving from $i = 1$ to $i = 0$ is seen for left side neighbors. This effect drives all the results on network measures in the bounded technological space in the following analysis section (section 2.4), where also figure 2.2 is discussed in more detail.

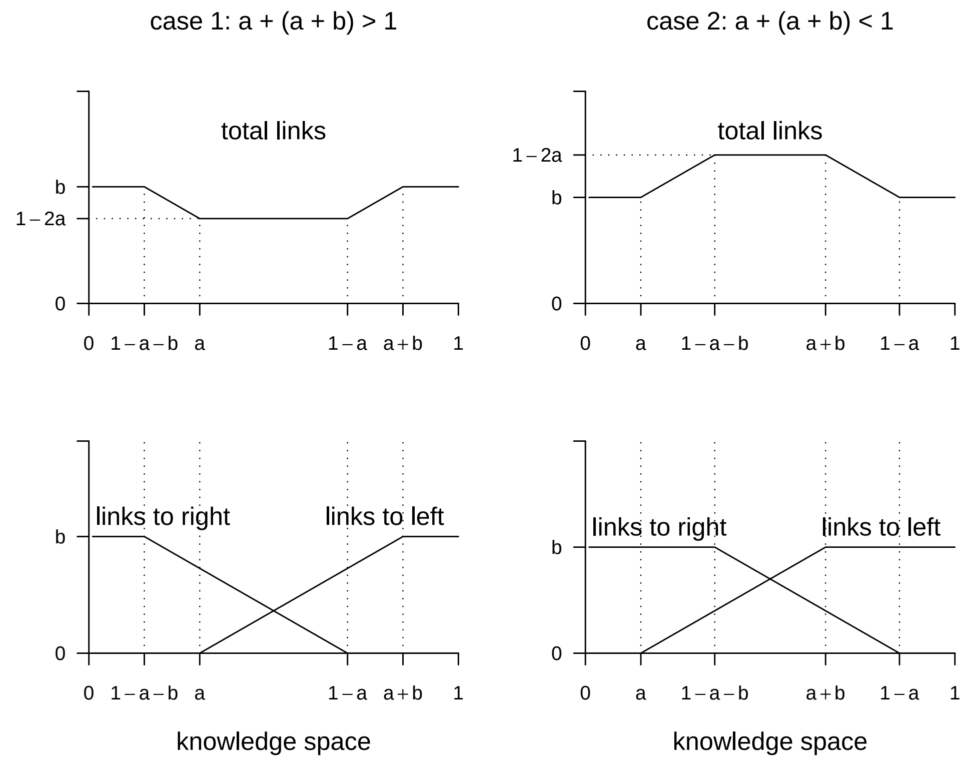

Figure 2.2: *Degree centrality as a function of position in the knowledge space. In the bounded knowledge space (the unit interval) the degree (total links) of the agent depends on its position. Firms with a central position in the knowledge space are less (more) central in the network in case 1 (case 2).*

The network is completely determined by the list of pairwise alliances, so in principle it is possible to derive any network characteristic from the assumptions on alliance formation. In this chapter however, we will focus on degree centrality, closeness centrality and clustering: three of the most common measures used in network analysis.

2.4 Analysis

2.4.1 Degree Centrality

The degree centrality of a node is simply the number of links it has to other nodes. It is thought relevant because a firm with many R&D alliances is highly engaged in knowledge generation (Ahuja, 2000), and alliances signal access to knowledge (or other resources) residing in the partnering firms (Arora and Gambardella, 1990).

Unbounded space In the unbounded knowledge space all firms are in the same situation. The agent at the origin, 0, forms links with all partners $j \in [-a-b, -a] \cup [a, a+b]$. In the model it is assumed that firms are uniformly distributed with density one.[2] Therefore the degree of agent 0 is calculated by integrating over its neighborhood which yields a degree of 2b. Because all firms are in the same situation, the degree distribution of the graph is a point mass at $2b$.

Bounded space In the bounded knowledge space the neighborhood of firm i may be restricted to the left, to the right, or both. This is taken into account in the following general expression for degree. Denote agent i's left neighborhood by N_i^1 with the lower left boundary B_i^{1l} and the upper left boundary B_i^{1u}. Similarly, denote agent i's right neighborhood by $N_i^2 = \left[B_i^{1l}, B_i^{1u}\right]$. Then the degree ($d_i$) of agent i is

$$d_i = N_i^1 + N_i^2 = \left(B_i^{1l} - B_i^{1u}\right) + \left(B_i^{2l} - B_i^{2u}\right). \tag{2.1}$$

The left and right neighborhood of agent i are restricted by the profitable range (a and $a+b$) and possibly by the boundaries of the knowledge space (0 and 1). Therefore

$$\begin{aligned} B_i^{1l} &= \max(0, i-a-b), & B_i^{1u} &= \max(0, i-a), \\ B_i^{2l} &= \min(1, i+a), & B_i^{2u} &= \min(1, i+a+b). \end{aligned} \tag{2.2}$$

If $a+b < 1$, firms near the left boundary are not restricted on the right and will have a full right neighborhood of size b ($B_i^{2l} = i+a$, $B_i^{2u} = i+a+b$). When moving to the right, however, at some point ($i+a+b > 1$), agents' right neighborhood's are bounded by 1

[2] Integration over the whole knowledge space yields the size of the firm population. Because the model assumes that the bounded knowledge space is the unit interval and firms are uniformly distributed with density one, the size of the population is one. Therefore, all results on sizes of a subpopulation denote a fraction of the total population.

($B_i^{2u} = 1$), and finally ($i + a > 1$), a right neighborhood becomes impossible ($B_i^{2l} = 1$). As the right boundary becomes more restrictive, the left boundary becomes less so. When moving right from the origin, eventually ($i \geq a$) agent i has a left neighborhood ($B_i^{1u} = i - a$).

Two cases Whether the gain of lefthand neighbors is higher than the loss of righthand neighbors depends on the size of the minimum and the maximum distance, i.e. a and $a + b$. Figure 2 shows both cases: if i) $a + (a + b) > 1$, agents moving away from zero restrict their right neighborhood before a left neighborhood forms. In this case, being more central in the knowledge space implies lower degree centrality. If ii) $a + (a + b) < 1$, agents moving away from zero form a left neighborhood before their right neighborhood becomes restricted. In this case, agents which are central in knowledge space are also central in their degree.

Distribution When the degree of each node is known, the degree distribution is gained simply by sorting the nodes according to their degree. Numerical calculations of degree formulas 2.1 and 2.2 allow for investigating the distributions occurring in parameter space $a = [0, 1] \times b = [0, 1]$, with $a + b \leq 1$. The result is given in figure 2.3, which depicts the first three moments of the degree distribution, i.e. mean, coefficient of variation (standard error / mean) and skewness. In each panel a line separates case 1, $a + (a + b) > 1$ from case 2, $a + (a + b) < 1$ (the right upper and the left lower parts of the panel respectively).

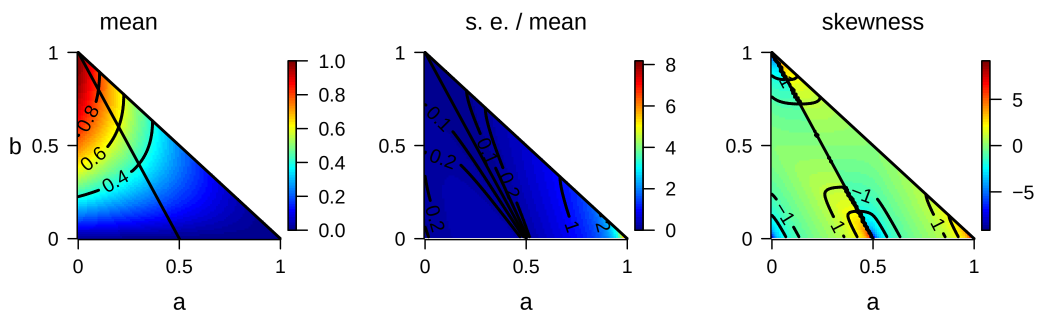

Figure 2.3: *Mean, coefficient of variation (s.e./mean) and skewness of degree distributions in parameter space. Calculations are based on 200 agents in the unit interval.*

Looking at the left panel, we see that the average mean of degree (the density of the graph) increases with b, the profitable range, and decreases with a, the minimum profitable distance. The transition from case 1 to case 2 is smooth and in both cases we find high and low mean of degree. The coefficient of variation (middle panel) is moderate being below 1 for most of the parameter space. Distributions are rather centered for large regions of the parameter space (green color in right panel).

A stylized fact of real-world networks is that mean degrees are low and degree distributions are right skewed. This is observed only for small b and $a \approx 0.5$. With respect to degree we therefore note that the model is more consistent with stylized facts in a small region of the parameter space.

2.4.2 Closeness Centrality

A node with high closeness centrality has short distances to other nodes in the network. This measure is critical when for example information flows among agents only over direct links in the network, and degrades with each transfer. In that situation, firms in a central position have good access to information and might be influential emitters of information (Singh, 2005). High average closeness in a network indicates the possibility of rapid spread of information.

Closeness centrality (c_i) of a node i is defined as the inverse of the node's average path length (p_i) to all other reachable nodes in the network

$$c_i = p_i^{-1} = \left(\frac{1}{N-1} \sum_{j=1, j \neq i}^{N} p_{ij} \right)^{-1},$$

where p_{ij} denotes the path length (network distance) between nodes i and j. This definition is equivalent to

$$c_i = \left(\frac{\sum_{s=1}^{\infty} s \, m_{i,s}}{\sum_{s=1}^{\infty} m_{i,s}} \right)^{-1}, \tag{2.3}$$

where $m_{i,s}$ is the mass of agents reachable in s steps (i.e. $j \ni p_{ij} = s$).

Unbounded space For calculation of the closeness coefficient (c_i) and average path length (p_i), it remains to derive the mass of agents $m_{i,s}$ reached within each step s. Considering first the unbounded knowledge space gives a good intuition of how an agent reaches other agents in knowledge space.

The logic is identical for all cases. Table 2.1 illustrates it for $a < b$. Agent 0 is representative of all agents and because of the left-right symmetric we need only look at agents to his right. At distance 1 are only his immediate neighbors, $[a, a+b]$. Using neighbor $2a$ he can reach $(0, a)$ in one (more) step. Using neighbor a he can reach $[2a, 2a+b]$ in one (more) step; using $a+b$ he can reach $[2a+b, 2a+2b]$. Thus, in 2 steps he reaches $(a+b, 2a+2b]$ (plus agents in $(0, a)$). Repeating this strategy we see that at each step he reaches an additional $a+b$ agents (except at step 2). This gives the total mass of agents for each step, m_s in equation 2.3.

Table 2.1: *Calculation of closeness centrality ($a < b$)*

Step s	From	To	Total area	Total mass m_s
1	0	$[a, a+b]$	$[a, a+b]$	b
2	$2a$ a $a+b$	$(0, a)$ $[2a, 2a+b]$ $[2a+b, 2a+2b]$	$(0, a) \cup (a+b, 2a+2b]$	$a+a+b$
3	$2a+b$ $2a+2b$	$[3a+b, 3a+2b]$ $[3a+2b, 3a+3b]$	$(2a+2b, 3a+3b]$	$a+b$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$

In each further step, agent 0 reaches two new intervals of size $a + b$ farther to the right and left in knowledge space, yielding $m_s = 2(a + b)\ \forall s > 3$. Of course, in the unbounded knowledge space each node accesses infinitely distant nodes and therefore the average path length becomes infinite and closeness centrality is not given.

Bounded space In the bounded knowledge space, calculation of average path length follows the same logic as for unbounded knowledge space. Each step s, a new interval is founded to the left (N_s^{2s-1}) and to the right (N_s^{2s}). In case $a > b$ there might exist a gap between accessed intervals, which might be closed by expanding surrounding intervals. Summing up the size of all intervals accessed in a certain step s allows for calculating the mass of agents reached within distance s,

$$
\begin{aligned}
m_1 &= |N_1^1| + |N_1^2|, \\
m_s &= \sum_{k=1}^{2s} |N_s^k| - m_{s-1} \quad \forall s > 1.
\end{aligned}
\tag{2.4}
$$

The difference with the unbounded knowledge space is that the process is restricted by the unit interval. Therefore, the boundaries of the kth interval in step s, N_s^k, are determined by i) the minimum and maximum profitable range (a and $a + b$), ii) existing boundaries of neighboring intervals (N_{s-1}^{k-2},N_{s-1}^{k+2}), or by iii) the boundaries of knowledge space (0, 1). Taking into account these restrictions yields general formulas for the lower boundaries ($B_s^{k,l}$) and upper boundaries ($B_s^{k,u}$) of newly founded intervals to the left

$$
\begin{aligned}
B_s^{2s-1,l} &= \max(0, B_{s-1}^{2s-3,l} - a - b), \\
B_s^{2s-1,u} &= \max(0, \min(\bar{B}_{s-1}^{2s-3,l}, B_{s-1}^{2s-3,u} - a)),
\end{aligned}
$$

to the right

$$
\begin{aligned}
B_s^{2s,l} &= \min(1, \max(\bar{B}_{s-1}^{2s-2,u}, B_{s-1}^{2s-2,l} + a)), \\
B_s^{2s,u} &= \min(1, B_{s-1}^{2s-2,u} + a + b),
\end{aligned}
$$

and expanded intervals in between

$$
\begin{aligned}
B_s^{k,l} &= \max(\bar{B}_{s-1}^{k-2,u}, \min(B_{s-1}^{k-2,l} + a, B_{s-1}^{k+2,l} - a - b)), \\
B_s^{k,u} &= \min(\bar{B}_{s-1}^{k+2,l}, \max(B_{s-1}^{k-2,u} + a + b, B_{s-1}^{k+2,u} - a)).
\end{aligned} \tag{2.5}
$$

Equation 2.4 in combination with equation 2.5 are applied in appendix A.1 to analyze the two cases and in the main text below to analyze distributions of closeness centrality in parameter space. Note that there are two kinds of boundaries in equation 2.5. Boundaries marked with a bar ($\bar{B}_s^{k,x}$) represent constraints imposed by neighboring intervals. Boundaries without bar ($B_s^{k,x}$) serve as stepping stones from which new agents may be reached. The algorithm in equation 2.5 may create empty intervals at the boundary of the knowledge space, with the upper and lower boundary being identical ($B_s^{k,l} = B_s^{k,u}$). Because empty intervals do not serve as stepping stones, one needs to set $B_k^{k,l} = B_s^{k,u} = \text{NULL}$ if $B_s^{k,l} = B_s^{k,u}$, resulting in neglecting all terms involving $B_s^{k,l}$ or $B_s^{k,u}$.

Two cases Figure 2.4 gives a numerical example of closeness centrality as a function of the agent's position in bounded knowledge space. The same cases as for degree are considered. The example illustrates results under the additional assumptions $a \leq b$ and $a \leq 1/3$. The effect of the additional assumptions is discussed after the example. Appendix A.1 provides a detailed mathematical discussion of the two cases.

First, consider **case 1** with $a + (a + b) > 1$. This case is illustrated on the left side of figure 2.4, where firms closer to the center of knowledge space have lower closeness centrality. This can be explained by noting two things. Firstly, under the assumptions that $a \leq b$ and $a \leq 1/3$ all agents reach all other agents in knowledge space in at most two steps.[3] This is because the profitable range is large ($b > 1/3$ by the case definition) and no gaps are created between accessed intervals (by $a \leq b$ and $a \leq 1/3$).

Secondly, in case 1, the size of the neighborhood is larger for agents closer to the boundary of knowledge space (see discussion of degree centrality). When all agents are reached within two steps, the size of the initial neighborhood drives all the results. Hence, agents closer to the boundary have shorter average path lengths and higher closeness centrality. More specifically, agents $i \leq 1-a-b$ have a full right neighborhood

[3] If a is too big and if b is too small, it is hard for an agent to reach agents who are too close. In the extreme, as $b \to 0$ it becomes possible only to reach agents at locations $i + ka$ where k is an integer.

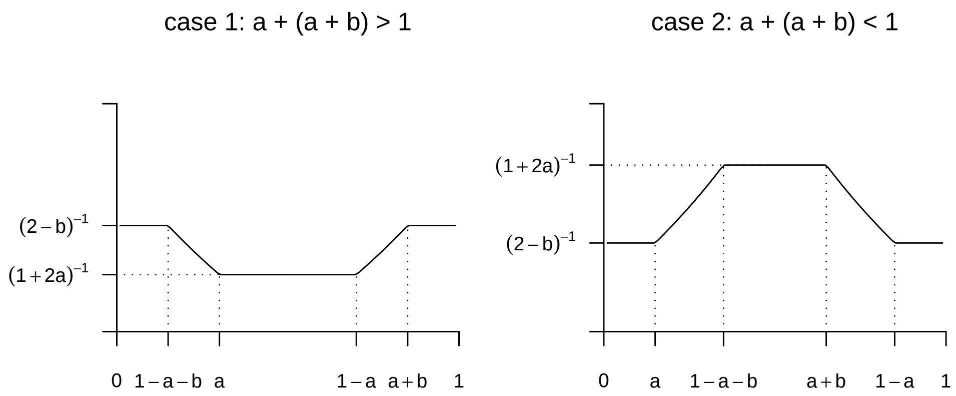

Figure 2.4: *Closeness centrality as a function of position in the knowledge space. In the bounded knowledge space (the unit interval) the closeness centrality of the agent depends on its position. Firms with a central position in the knowledge space are less (more) central in the network in case 1 (case 2).*

of size b. As all other neighbors are reached in the next step, their average path length is $b + 2(1 - b) = 2 - b$. Agents $1 - a - b < i < a$ obtain an average path length of $1 + i + a$ and agents $a \leq i \leq 0.5$ an average path length of $1 + 2a$ which is lower (see appendix A.1 for derivations).

However the assumptions $a \leq b$ and $a \leq 1/3$ are necessary for obtaining this result. If $1/3 < a < 1/2$, agents $\in [1 - 2a, a)$ need three steps to reach all other agents in knowledge space, whereas agents $\in [0, 1 - 2a] \cup [a, 0.5]$ only need two steps. In the first step, agent $i \in [1 - 2a, a)$ reaches its neighborhood $[i + a, 1]$. In the second step, it reaches agents in $[0, 1 - a]$. Because $a > 1/3$, $1 - a < i + a$ and a gap exists between the two intervals. This gap is closed in the third step, yielding an average path length of $3a + 2i$. Note that as agent i approaches a, the average path length becomes $3a+2a = 5a$ which is larger than the average path length $1+2a$ of agents $i \in [a, 0.5]$ for $1/3 < a < 1/2$. Therefore, closeness centrality becomes a non-continuous function of the position in knowledge space. It is highest for agents at the boundary and decreases to its minimum as i goes to a. At a closeness centrality jumps to a higher level which is maintained until the center of knowledge space. For $1/2 < a$ agents $[1 - a, a]$ with undefined closeness centrality.

The second condition, $a \leq b$, has been used several times to obtain the example result. If $a > b$ the size of the initial neighborhood becomes less important relative to how efficiently further agents are reached subsequently. Numerical calculation show that closeness centrality becomes a non-continuous function of the position in knowledge space, and for some parameter ranges agents at the center of knowledge space may have higher closeness centrality than agents at the boundary of knowledge space.

Now, consider **case 2** with $a + (a + b) < 1$. The right side of figure 2.4 illustrates this case under the additional condition $a \leq b$ (see appendix for derivations). We find that agents closer to the center of knowledge space have shorter average path lengths and higher closeness centrality. The reason is that i) agents closer to the center of the knowledge space reach more agents in the first step than agents at the boundary (see degree section above) as well as ii) all subsequent steps. This is because in the second step, the interval surrounding agent i ($[max(0, i - a), min(1, i + a)]$) is reached and from the second step on, agents farther to the left and right are accessed with speed $a + b$ until the boundaries of knowledge space are reached. The agent at the center accesses in all steps agents to the right and to the left and reaches both boundaries in the same number of steps. The closer an agent to a boundary of knowledge space, the smaller the number of steps where the agent accesses agents to its left and to its right. Therefore, agents in the center have higher closeness centrality than agents at the boundary.

However, as for case 1, the condition $a \leq b$ is necessary for obtaining the relationship between closeness centrality and the position in knowledge space. If $a > b$, closeness centrality becomes a non-continuous function of knowledge space and for some parameter settings agents at the boundary have slightly higher closeness centrality as agents at the center of knowledge space.

Distribution Numerical calculations provide insights on the occurrence of closeness distributions in the parameter space $a = [0, 0.5] \times b = [0, 1]$, with $a + b < 1$.[4] The implementation is based on the formulas for closeness (formulas 2.4 and 2.5). Because

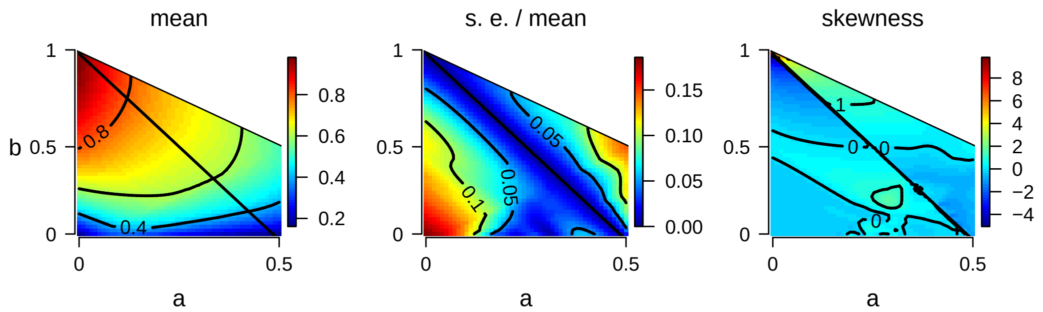

Figure 2.5: *Mean, coefficient of variation (s.e./mean) and skewness of closeness distributions in parameter space. Calculations are based on 200 agents in the unit interval.*

average closeness increases with the size of the initial neighborhood, we observe the

[4]The parameter space is chosen in order to avoid isolates. Closeness is not defined for isolates.

same pattern for the mean of closeness as for average degree, i.e. increasing with b and decreasing with a (see left panel of figure 2.5). coefficient of variation of closeness (middle panel of figure 2.5) is on a very low level overall, i.e. < 0.2. However, higher coefficients of variation are obtained for larger a and b in case 1 (upper right part of middle panel) and smaller a and b in case 2 (lower left part of middle panel). The distributions are centered and moderately skewed ($< |1|$) in large parts of the parameter space (right panel). High skewness as observed for large b and small a is exceptional. However, the tendencies for skewness are rather similar as observed for the corresponding degree distribution in figure 2.3.

Summary The results for both cases may be summarized as follows. Given the additional conditions $a \leq b$ and $a \leq 1/3$, we obtain the same result as for degree. In case 1 (case 2), agents which are positioned closer to the center of the knowledge space have lower (higher) closeness centrality in the network. The additional conditions affect global optima and continuity of closeness centrality. In case 1, with $a > 1/3$ the global minimum of closeness centrality is observed between the boundary and the center of knowledge space. In both cases, with $a > b$ closeness centrality typically is a non-continuous function in technological space with optima between the boundary and the center.

The distributions of the closeness coefficient in parameter space parallel the findings for degree. The reason is that path lengths are short in large regions of the parameter space and therefore the size of the initial neighborhood, degree, largely determines closeness centrality. However, closeness distributions have lower coefficients of variation and are less skewed than degree distributions.

2.4.3 Clustering Coefficient

The clustering coefficient of a node quantifies how close its immediate neighborhood is to being fully connected. In small-world networks average closeness and average clustering both are high (Watts and Strogatz, 1998). Whereas high closeness enables fast diffusion of knowledge, high clustering might foster knowledge generation due to specialization of groups of firms (Cowan and Jonard, 2004). From a social perspective, high clustering may indicate the effect of referrals in a network. For example networks of friendship relations are often highly clustered.

The clustering coefficient (c_i) of a node i is defined as the number of links among its neighbors (e_i) divided by all links that possibly could exist among them ($1/2d_i^2$), i.e.[5]

$$c_i = \frac{2e_i}{d_i^2}. \tag{2.6}$$

[5] This definition does not correct for self-reflexivity because we consider a continuous distribution of agents in knowledge space.

Each link between two neighbors closes a triangle, which includes the focal agent and its two neighbors. Therefore, e_i, the number of links among agent i's neighbors, is also referred to as the number of triangles (or short triangles). Because the number of triangles is a network measure in its own right, results for both are given in the following.

Unbounded space In the unbounded knowledge space one might again consider agent 0 as the representative agent. Agent 0 has a neighborhood of size $2b$, equally divided into a left and a right neighborhood of size b. A fully connected graph of size $2b$ contains $1/2(2b)^2 = 2b^2$ links. However, the minimum distance a prevents the agents in the right (left) neighborhood to fully connect among each other. Similarly, the benefit range prevents some connections between left and right neighbors.

First, consider the number of links among right-hand neighbors of agent 0. Agent 0 has the right neighborhood $N_0^2 = [a, a+b]$. For each agent $j \in N_0^2$, the distance-benefit range determines the connections to other agents $k \in N_0^2$. If $a > b$, agent j connects to no other agent in the neighborhood of agent 0 and the clustering coefficient is zero. If $a \leq b$ clustering occurs because the neighborhoods of agents 0 and j overlap. To avoid the double counting due to bi-directional links, we consider only the right neighborhood of agent j. Agent 0 and j's right neighborhoods overlap in the interval $[j+a, a+b]$ as long as $j < b$. The size of the overlap is $(a+b)-(j+a) = b-j$. Knowing the size of the overlap for each agent, we obtain the number of triangles among agent 0's right neighbors (e_0^r) by integrating over all agents which possibly contribute to clustering, i.e. $e_i^r = \int_a^b (b-j)\mathrm{d}j = 1/2(b-a)^2$. The number of triangles among agent 0's left neighbors (e_0^l) is symmetric. The number of links between left- and right-hand neighbors (e_0^{lr}), is similarly derived. Note first that some left-hand neighbors j of agent 0 have a right neighborhood which overlaps with the right neighborhood of agent 0, if $a \leq b$. The overlap is $[a, j+a+b]$, if $j > -b$. Integration over agents j contributing to left-to-right clustering yields $e_0^{lr} == \int_{-b}^{-a}(j+b)\mathrm{d}j = 1/2(b-a)^2$. Summing the triangles gives total triangles of $3/2(b-a)^2$. Normalizing triangles by the number of potential links ($2b^2$) gives the clustering coefficient of $\frac{3(b-a)^2}{4b^2}$.

Bounded space In the bounded knowledge space, the calculation of clustering follows the same logic as for unbounded knowledge space. However the overlap of neighborhoods and the boundaries of integration depend on the position of the agents. Therefore, it is convenient first to express the clustering coefficient rather generally: agent i possibly has a left and a right neighborhood. As in the unbounded knowledge space, the total number of triangles (e_i) is the sum over left triangles (e_i^l), right triangles (e_i^r)

and left-to-right triangles (e_i^{lr}).

$$e_i = \underbrace{\int_{B_i^{1l}}^{max(B_i^{1u}-a,B_i^{1l})} (B_i^{1u} - B_j^{2l})\,\mathrm{d}j}_{e_i^l} + \underbrace{\int_{B_i^{2l}}^{max(B_i^{2u}-a,B_i^{2l})} (B_i^{2u} - B_j^{2l})\,\mathrm{d}j}_{e_i^r} + \underbrace{\int_{\max(0,\min(B_i^{2l}-a-b,B_i^{1u}))}^{B_i^{1u}} (B_j^{2u} - B_i^{2l})\,\mathrm{d}j}_{e_i^{lr}} \quad (2.7)$$

where for example B_i^{1l} is the lower boundary (indexed by l) of agent i's left (indexed by 1) neighborhood and B_j^{2u} is the upper boundary (indexed by u) of agent j's right (indexed by 2) neighborhood. These boundaries are determined by the benefit-distance range and the size of the knowledge space, exact formulas are given in the degree section 2.4.1, equation 2.2. Note that max-, min-expressions restrict integration over those agents which contribute to clustering. Recall that in the unbounded space, a necessary condition for clustering to occur has been $a \leq b$. If $a > b$, then for example right neighbors can not connect within agent i's right neighborhood nor reach agent i's left neighborhood. In bounded knowledge space, the condition $a \leq 0.5$ also is necessary for clustering. If $a > 0.5$, agent i has only a left or right neighborhood which is of size smaller than a.

Two cases Figure 2.6 gives an example of the clustering coefficient as a function of the agent's position in bounded knowledge space. The same two cases as for degree and closeness centrality are considered. The two cases are discussed qualitatively on the example given in figure 2.6. Appendix A.2 verifies that the qualitative results gained from the example hold in general for triangles and clustering. The lower left panel of figure 2.6 depicts the number of left, right and left-to-right triangles for each agent i in knowledge space. An agent i close to the boundary of knowledge space ($i \leq 1 - a - b$) has a complete right neighborhood and no left neighborhood. The right neighborhood yields $1/2(b-a)^2$ triangles. A result already derived for the unbounded knowledge space. Moving further to the right, from ($i > 1 - a - b$) the right neighborhood becomes restricted by the upper boundary of knowledge space, and therefore the number of connections among right-hand neighbors decreases. For $i > 1 - 2a$ right triangles are zero because the right neighborhood of agent i has a size smaller than a. Then right-hand neighbors are too close to connect to each other. The situation is symmetric for left triangles. The third kind of connections among

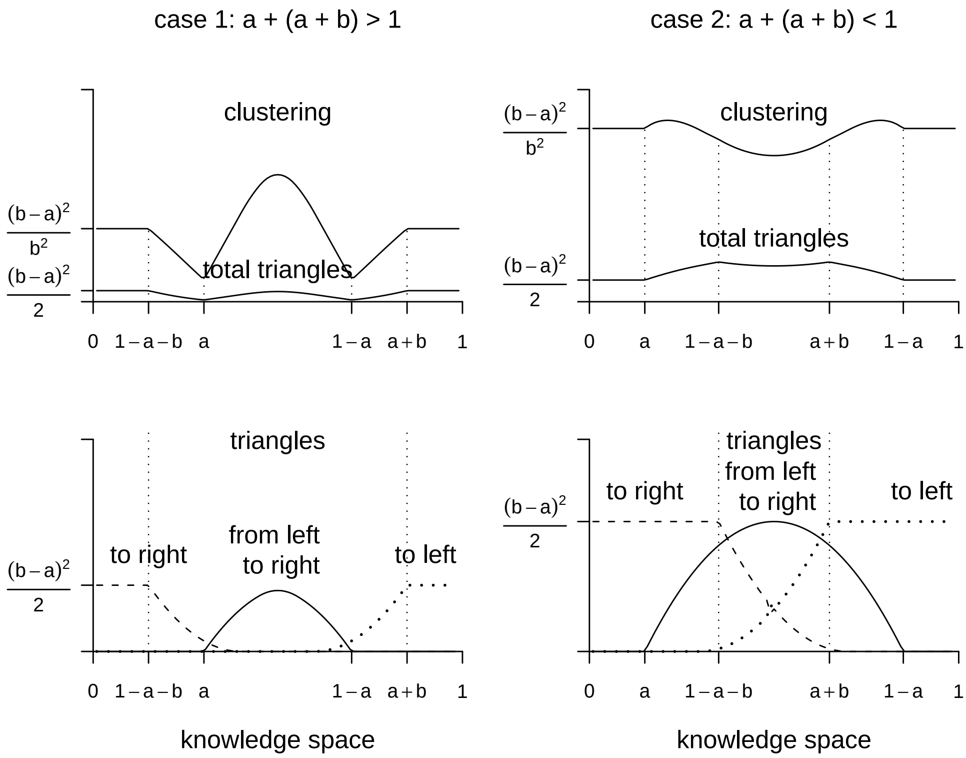

Figure 2.6: *Clustering coefficient as a function of position in the knowledge space. In the bounded knowledge space (the unit interval) the clustering coefficient of the agent depends on its position. Firms with a central position in the knowledge space have higher (lower) clustering coefficient in the network in case 1 (case 2).*

neighbors are left-to-right triangles. Of course, left-to-right triangles may only exist if both neighborhoods exist (i.e. if $a \leq i \leq 1-a$). Moving from a further to the right, left-to-right triangles increase. They attain their maximum of $1/2(b-a)^2$ if the left and right neighborhood contains all agents which connect to the other neighborhood (i.e. if $b \leq i \leq 1-b$). Note that this maximum is never attained if $b > 0.5$. For $1-b < i < 0.5$, agent i's right-hand neighbors are removed as left-hand neighbors are added. The increase of left-to-right triangles is only due to symmetry gains.

Case 1, $a + (a+b) > 1$, is depicted at the left side of figure 2.6. Summing up all three kinds of triangles (e_i^l, e_i^r, e_i^{lr}) gives the total number of triangles (e_i) of agent i (the lower line in the upper left panel). In the example, increasing i from zero, the number of triangles first remains stable at $1/2(b-a)^2$. When moving to the right from some point ($1-a-b < i$) the number of triangles decreases as the right neighborhood is restricted and later on ($a \leq i$) increases again when the left neighborhood forms.[6] A symmetric pattern appears when decreasing i from one. Clustering takes a similar shape as triangles (see left upper panel). Appendix A.2 shows that clustering follows a similar pattern.[7]

Case 2, $a + (a+b) < 1$, is illustrated at the right side of figure 2.6. The case condition now implies that total number of triangles first remains stable for $i < a$, and then increases for $a \leq i < 1-a-b$ (see upper right panel). Then, for $1-a-b \leq i$, the total number of triangles slightly decreases when moving towards the center of knowledge space. Clustering also first increases and then decreases again. However, the decrease starts within the interval $[a, 1-a-b]$. Appendix A.2 validates that in the interval $(1-a-b, 0.5]$ triangles always decrease or remain stable with i. Furthermore, it is shown that the shape of clustering as depicted in figure 2.6 is typical for case 2.

Because both the number of triangles and clustering are non-monotonic functions of the firm position in knowledge space, it is of interest where we observe their global optima. The various cases make analytical derivation tedious. Therefore, we analyze the functions numerically by implementing the general formulas for triangles and clustering, i.e. equations 2.6 and 2.7. Calculations are done for the complete parameter space[8] $a = [0, 0.5] \times b = [0, 1]$, with $a + b \leq 1$. Numerical calculations show that the example of figure 2.6 represents the general case well. In case 1 (case 2), the maximum (minimum) of triangles is obtained by agents at the boundary and the minimum (maximum) of triangles is obtained by agents between the boundary and center of the knowledge space. Clustering equals triangles normalized by degree and therefore

[6] Appendix A.2 shows that, from a on, decrease of right triangles is always outweighed by an increase of left-to-right hand triangles.

[7] The working condition $a + b < 1$ has no effect on the general pattern of clustering and triangles described above. The only difference is that the regime $[0, 1-a-b]$ where triangles and clustering is stable drops out. Instead, the number of triangles and the clustering coefficient decrease from the beginning and increase again from point a on.

[8] The parameter space is complete because no clustering occurs for $a > b$.

follows a different pattern. In case 1 (case 2), the maximum[9] (minimum) clustering is obtained by agents in the center of knowledge space and the minimum (maximum) clustering is obtained by agents between the boundary and center of the knowledge space.

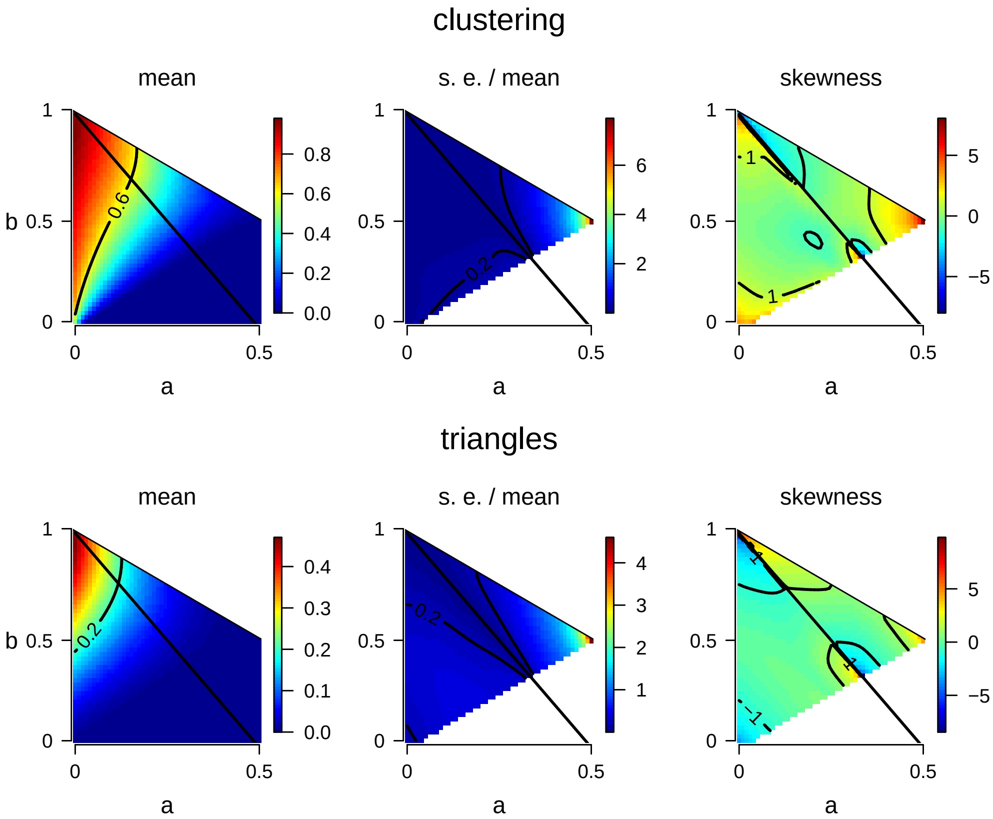

Figure 2.7: *Mean, coefficient of variation (s.e./mean) and skewness in parameter space. Calculations are based on 200 agents in the unit interval.*

Distribution Triangle and clustering distributions are depicted in figure 2.7. Triangle and closeness distributions have a similar pattern in parameter space with respect to their mean and coefficient of variation (see left and middle panels). The two cases imply similar levels of mean and coefficient of variation. The transition from one case to the other is smooth (crossing the diagonal line in left and middle panels). For triangles in the lower right panel, we find that the distribution is left skewed or centered for

[9]Only in some isolated cases with a small and b large (e.g. $a = 0.2$, $b = 0.75$) firms at the boundary of knowledge space have a slightly higher clustering coefficient.

most parameter settings. This means that mostly, many agents have relatively high number of triangles and few agents have low number of triangles. Note that skewness is opposite for clustering due to the normalization by the potential number of triangles (for $a < 0.4$).

Table 2.2: *Slopes and optima of clustering (c_i) and triangles (e_i) in two cases*[a]

	Case 1 ($a + (a + b) > 1$)			Case 2 ($a + (a + b) < 1$)		
$i \in$	$[0, 1 - a - b)$	$[1 - a - b, a)$	$[a, 0.5]$	$[0, a)$	$[a, 1 - a - b)$	$[1 - a - b, 0.5]$
$\partial e_i/\partial i$	0	$-, 0$	$+, 0$	0	$+$	$-, 0$
$\partial c_i/\partial i$	0	$-, 0$	$+, 0$	0	$+, -$	$-, 0$
Optima e_i	max	min	–	min	max	–
Optima c_i	–	min	max	–	max	min

[a] Reading example: in case 2, interval $[a, 1 - a - b)$, the slope of the clustering coefficient ($\partial c_i/\partial i$) is first increasing and later decreasing.

Summary In case 1 (case 2), agents at the boundary of knowledge space have the maximum (minimum) number of triangles. Moving towards the center of knowledge space, the number of triangles first decreases (increases) and later increases (decreases) again. Clustering follows the same pattern but the maximum (minimum) is attained for agents in the center. In case 1 (case 2) agents at an intermediate position between the boundary and the center of the knowledge space obtain the minimum (maximum) number of triangles and clustering coefficient. This result is summarized in table 2.2 and visible in figure 2.6.

2.5 Discussion

This model gives us an intuition about how the benefit-distance relationship affects network formation. The analysis demonstrates how the agent's position in the network becomes a function of its position in knowledge space. Furthermore, the analysis of the distributions of network measures showed that the overall network structure depends on the benefit-distance relationship. A comparison of the three network measures, triangles, closeness and degree, reveals that the three are closely related. All three network measures take a similar shape as a function of the position in technological space (compare figures 2.2, 2.4 and 2.6). Furthermore, the pattern of their distributions over the parameter space are similar with respect to the first three moments (compare figures 2.3, 2.5 and 2.7). One reason is that the network measures are related in network space. For example degree partly determines the closeness coefficient. However, another reason is that the model determines the relationships of the agents in the network according to their relationships in knowledge space, moderated by the benefit-distance effect. For example if alliance formation is beneficial for technologically close firm-pairs, high clustering occurs because the agent and its neighbors are all close in knowledge space.

The result is that agents which have high degree centrality also have high closeness centrality and relatively high number of triangles. Furthermore, some regions in parameter space generate networks with high average closeness centrality as well as high clustering; defining characteristics of small world networks (Watts and Strogatz, 1998). However, different to the rewiring model of Watts and Strogatz (1998), where neighboring agents in a ring are linked and short cuts are introduced by random rewiring, our model obtains high clustering and short path length because of the agent's preference to connect to agents within a larger region of the structuring (knowledge) space. Therefore, when the network has high average closeness and clustering, it is also dense. This contradicts stylized facts on small world networks, which usually are sparse.

The central result of the analysis, however, is that we observe two different regimes at the level of the agent. If small (large) technological distances are profitable, then agents in the center (at the boundary) of technological space are more central in the network. Whether this intuition is correct depends on the assumptions of the model. Would we gain the same intuition from alternative, more realistic assumptions?

For discussing this question, first recall the main building blocks of the model. In the model, a population of identical agents are uniformly distributed in technological space. The value of an alliance depends on the technological distance between the firm-pair. If the technological distance between the firm-pair is within a profitable range, the firm-pair forms an alliance. These building blocks express several assumptions regarding the knowledge space, the population of agents and their decision making. The central assumptions concern the modeling of technological space and the benefit of alliance formation. This is where we focus our attention in the following chapters. Further issues such as (in-)complete information of the agents and development of a dynamic model would rather shift the focus of the analysis than alter our findings of the analysis.

The assumption of a one-dimensional knowledge space is a simplification which does not seem to alter the results. Agents in the center of a multi-dimensional technological space are still less (more) restricted in alliance formation than agents at a boundary, if technological proximity (distance) is preferred. The intuition holds also for arbitrary distributions of agents in technological space. It is probably true that some regions in technological space are more crowded than others and that this is likely to affect alliance formation (Stuart, 1998). Allowing for arbitrary distributions would be a generalization of the model which would simply add an effect. Then, the number of alliances of an agent depends on the distribution of firms in knowledge space and the boundaries of knowledge space. The relationship between the three network measures would be similar as for the uniform distribution.

The assumption of an inverse-U-shaped relationship between technological distance and benefit of joint knowledge creation is theoretically justified (Cohen and Levinthal, 1990) and empirically grounded (Mowery et al., 1998). Of course, alliances depend on many other factors (Ahuja, 2000) but these do not necessarily alter the benefit-distance effect. However, because in the model the value of an alliance depends uniquely on the technological distance between the firm-pair, each alliance decision is independent from all other (potential) alliances in the network. This assumption of independence of alliance formation includes two issues. First, the alliance decision of one agent is independent from alliances formed by other agents. Second, the agent decides on each alliance independent from other alliances it might potentially form.

The first issue arises because there are no indirect effects of alliance formation. Empirical work suggests that indirect links affect the firms' innovative performance (Ahuja, 2000), whereas in the model, alliances of third parties are not taken into account in decision making. The argument which justifies this assumption is that we model joint knowledge creation and not information spill-overs and that direct links are relatively more important for innovative performance than indirect links (Ahuja, 2000, p.449). However, introducing indirect benefits would change the analysis and the results. The analysis would change because with interdependent alliance formation one would expect to find multiple equilibria of network configurations (as e.g. in Gilles and Johnson, 2000). The resulting networks would change because indirect benefits motivate agents to increase their closeness centrality. This fosters the creation of short-cuts in the network, which results in less skewed closeness distributions.

The second issue arises because the decision of a firm-pair is modeled rather than the decision of a firm on its alliance portfolio. Of course, the strategic variable used to maximize the benefit of the firm is its alliance portfolio (e.g. Ozcan and Eisenhardt, 2009). The assumption that each alliance is considered in isolation excludes for example congestion effects, where the sheer number of alliances would negatively affect the value of additional alliances. Furthermore, novelty gain is likely to decrease with the number of partners having similar knowledge. If a technologically distant partner is chosen for high novelty gain, then a second partner with similar knowledge yields lower novelty gain. This effect is not in the model but would alter the network structure fundamentally. In the model, agents partner with whole fractions of the population whereas with decreasing returns agents would rather partner with individual agents for which the distance-benefit effect is highest. This could result in relatively sparse networks with lower average closeness and lower clustering than in the original model but probably it would not affect the qualitative results.

Seen in this light, the model describes the agent's opportunities for alliance formation which are given by its position in the knowledge space together with the distance-benefit effect. Some agents are in a richer environment than others, in the sense that they face more agents with which alliance formation would be (technologically) reasonable. Realization of alliances would then result from optimizing the alliance portfolio. However, this in fact changes only slightly the intuition gained from the model. Those agents which have more opportunities for alliance formation are in a better position to become central in the network.

2.6 Conclusion

This chapter proposes a theoretical model which shows how the technological position of firms affects network formation. In the model, we assume an inverse-U-shaped relationship between distance and benefit for two firms forming an alliance. The microeconomic foundation of this assumption is the trade-off between absorptive capacity and novelty gain (Cohen and Levinthal, 1990; Nooteboom et al., 2007). Mowery et al. (1998) confirmed the existence of this inverse-U-shaped benefit-distance effect on joint venture formation.

The theoretical model shows how certain benefit-distance specifications affect the network structure and firm positions. The model can be seen as a specification of the spatial social network, which is in the communication network tradition (Gilles and Johnson, 2000), or as a simplification of the evolutionary knowledge portfolio model of Cowan and Jonard (2009). The value of simplifying is less in giving analytical solutions but in shifting the focus from the overall network structure towards the firm network position. The main insight of the theoretical analysis is that a strong preference for technological proximity (distance) implies that firms which are in the center (at the boundary) of the knowledge space are going to be central in the research network.

Theoretical results on the network structure do not show a strong regime shift as is the case for the firm network position. In both cases, whether short or long technological distance makes a bilateral alliance beneficial, global network statistics may be skewed on higher as well as lower levels.

APPENDIX A

Derivation of Network Measures

A.1 Closeness Centrality

This section gives expressions for closeness centrality depending on the agents position in knowledge space. Application of the general formulas 2.4 and 2.5 necessitates auxiliary conditions besides the case conditions. To derive explicit expressions of closeness, we apply those conditions which correspond to the example in the main text, figure 2.4. Then the effect of the auxiliary conditions is discussed.

Two cases **Case 1**, $(a > 1 - a - b)$: In order to apply the general formulas 2.4 and 2.5, auxiliary conditions are needed. We specify three auxiliary conditions: i) $a + b < 1$, there exist agents with one complete left or right neighborhood, ii) $a \leq 0.5$, the graph has no isolates, and iii) $a \leq b$, no gaps exist between newly founded intervals (see discussion of how agents reach other agents in knowledge space in the main text, described in table 2.1).

Given these conditions there are three kinds of agents within the interval $[0, 0.5]$. Agents with complete right neighborhood but no left neighborhood, $[0, 1 - a - b]$, agents with restricted right neighborhood and no left neighborhood, $(1 - a - b, a)$, and agents with restricted left and right neighborhood, $[a, 0.5]$.

For agents $i \in [0, 1 - a - b]$ the boundaries in the first step become

$$B_1^{1l} = 0, \qquad B_1^{1u} = 0, \qquad B_1^{2l} = i + a, \qquad B_1^{2u} = i + a + b,$$

yielding $m_{d=1} = b$. The boundaries of the second step are obtained by inserting the boundaries of the first step into equation 2.5.

$$\begin{aligned}
B_2^{3l} &= \max(0, \mathrm{NULL} - a - b) = 0, \\
B_2^{3u} &= \max(0, \min(0, \mathrm{NULL} - a)) = 0, \\
B_2^{4l} &= \min(1, \max(i + a + b, i + 2a))) = i + a + b && \text{by } a \leq b, \\
B_2^{4u} &= \min(1, i + 2(a + b)) = 1 && \text{by case 1}, \\
B_2^{0l} &= \max(0, \min(i - b, \mathrm{NULL} + a)) = 0 && \text{by } a \leq b, \\
B_2^{0u} &= \min(i + a, \max(\mathrm{NULL} + a + b, i + b)) = i + a && \text{by } a \leq b.
\end{aligned}$$

This yields $m_{d=2} = 1 - (i + a + b) + (i + a) - 0 = 1 - b$. Obviously, within two steps all nodes are reached giving an average shortest path of $p = b + 2(1 - b) = 2 - b$.

The average path length of agents $i \in (1 - a - b, a)$ is similarly derived. The boundaries of the first and second step are

$$\begin{aligned}
B_1^{1l} &= 0, & B_1^{1u} &= 0, & B_1^{2l} &= i + a, & B_1^{2u} &= 1, \\
B_2^{3l} &= 0, & B_2^{3u} &= 0, & B_2^{4l} &= 1, & B_2^{4u} &= 1,
\end{aligned}$$

$$B_2^{0l} = 0, \qquad B_2^{0u} = \begin{cases} i + a & \text{if } i \leq 1 - 2a, \\ 1 - a & \text{else.} \end{cases}$$

The last equation B_2^{0u} distinguishes two subcases. Given that $a > 1/3$, there are agents $i \in (1 - 2a, a)$ for which $B_2^{0u} = 1 - a$. They need to access the remaining $m_{i,s=3} = (i + a) - (1 - a)$ agents in a third step. This results in an average path length of

$$p = \begin{cases} 1 + i + a & \text{for } i \in (1 - a - b, a), \text{ if } a \leq 1/3 \\ 1 + i + a & \text{for } i \in (1 - a - b, 1 - 2a], \text{ if } a > 1/3, \\ 3a + 2i & \text{for } i \in (1 - 2a, a), \text{ if } a > 1/3. \end{cases}$$

The interesting result here is that for both $a > 1/3$ and $a \leq 1/3$, the average path length increases with i over the whole interval $(1 - a - b, a)$.

Agents $i \in [a, 0.5]$ have the boundaries

$$\begin{aligned}
B_1^{1l} &= 0 & B_1^{1u} &= i - a & B_1^{2l} &= i + a & B_1^{2u} &= 1 \\
B_2^{3l} &= 0 & B_2^{3u} &= 0 & B_2^{4l} &= 1 & B_2^{4u} &= 1 \\
B_2^{0l} &= i - a & B_2^{0u} &= i + a,
\end{aligned}$$

which yields $m_{d=1} = 1 - 2a$, $m_{d=2} = 2a$ and $d = 1 + 2a$ for all agents $i \in [a, 0.5]$. Collecting the results on average path length and taking the inverse gives an overview on closeness centrality as a function of the position in knowledge space

$$c = p^{-1} = \begin{cases} (2-b)^{-1} & \text{for } i \in [0, 1-a-b], \\ (1+i+a)^{-1} & \text{for } i \in (1-a-b, a), \text{ if } a \leq 1/3, \\ (1+i+a)^{-1} & \text{for } i \in (1-a-b, 1-2a], \text{ if } a > 1/3, \\ (3a+2i)^{-1} & \text{for } i \in (1-2a, a), \text{ if } a > 1/3, \\ (1+2a)^{-1} & \text{for } i \in [a, 0.5]. \end{cases}$$

Comparing closeness centrality for different agents, we find that agents at the boundary have higher closeness centrality than firms at the center of knowledge space ($(2-b)^{-1} > (1+2a)^{-1}$ by the case condition). Furthermore, within the interval $(1-a-b, a)$ closeness centrality decreases monotonically with i. If $a \leq 1/3$, closeness centrality is a continuous and monotonically decreasing function from the boundary to the center of the knowledge space. For $a > 1/3$ closeness centrality becomes a non-continuous and non-monotonic function of position in knowledge space. There is a jump at position a from $(3a+2i)^{-1}$ up to $(1+2a)^{-1}$.

To what extent are the auxiliary conditions necessary to obtain the results that i) agents at the boundary have higher closeness centrality than agents at the center and ii) closeness centrality decreases monotonically and continuously from the boundary to the center of the knowledge space? To see this, in the following we drop each of the conditions while maintaining the others.

Condition i) $a+b < 1$ generates two groups of agents, $[0, 1-a-b]$ and $(1-a-b, a)$. The alternative specification, $a+b \geq 1$, would imply that $1-a-b \leq 0$. This has the only effect that the formula for closeness which has been previously derived for agents $i \in (1-a-b, a)$ now applies to all agents $i \in [0, a)$. Hence, this condition does not affect the results.

Condition ii) $a \leq 0.5$ affects the partitioning of knowledge space and has been used to derive interval boundaries. Alternatively, we may specify $a > 0.5$, keep condition iii), $a \leq b$, and drop condition i) $a+b < 1$. Then, agents of the two intervals, $[0, 1-a]$ and $(1-a, 0.5]$, need to be distinguished. Agents $i \in (1-a, 0.5]$ are isolates, for which we set closeness centrality to zero. Agent $i \in [0, 1-a]$ reaches all other connected agents within three steps. Its right neighborhood, step 1, is $[i+a, 1]$. In the second step, via agent 1, agent i reaches $[0, 1-a]$. In the final, third step, via agent 0 all remaining agents $i \in [1-a, i+a]$ are reached. This results in an average path length of $p = 1-(i+a)+2(1-a)+3(i+a-a) = 3-3a+2i$. The inverse, closeness centrality, decreases monotonically with i and there is a jump down to zero at position a. Hence, this condition does not affect the results.

Condition iii) $a \leq b$ ensures that closeness centrality is a monotonic and continuous function from the boundary to the center of knowledge space. For $a > b$ closeness centrality in general is non-continuous. Numerical calculations show that global minima and maxima of closeness centrality might be obtained between the boundary and center of the knowledge space. The reason is that if $a > b$ there are gaps between newly founded intervals and agents in between might expand intervals more efficiently. However, in case 1, closeness centrality is always higher or as high for agent 0 at the boundary than for agent 0.5 in the center of knowledge space.

Case 2 ($a < 1 - a - b$): In this case some agents have a restricted left neighborhood and a complete right neighborhood. Given the auxiliary conditions i) $1/2 \leq (a + b)$ and ii) $a \leq b$, we derive the boundaries for agents of the intervals $[0, a), [a, 1 - a - b], (1 - a - b, 0.5]$. For agents $i \in [0, a)$ these are

$$\begin{array}{llll} B_1^{1l} = 0 & B_1^{1u} = 0 & B_1^{2l} = i + a & B_1^{2u} = i + a + b \\ B_2^{3l} = 0 & B_2^{3u} = 0 & B_2^{4l} = i + a + b & B_2^{4u} = 1 \\ B_2^{0l} = 0 & B_2^{0u} = i - a & & \end{array}$$

yielding an average shortest path of $p_i = b + 2(i + a + 1 - (i + a + b)) = 2 - b$. For agents $i \in [a, 1 - a - b]$ the boundaries are

$$\begin{array}{llll} B_1^{1l} = 0 & B_1^{1u} = i - a & B_1^{2l} = i + a & B_1^{2u} = i + a + b \\ B_2^{3l} = 0 & B_2^{3u} = 0 & B_2^{4l} = i + a + b & B_2^{4u} = 1 \\ B_2^{0l} = i - a & B_2^{0u} = i + a & & \end{array}$$

yielding an average shortest path of $p_i = (i-a)+b+2((i+a)-(i-a))+1-(i+a+b)) = 2 + a - b - i$. For agents $i \in (1 - a - b, 0.5]$ the boundaries are

$$\begin{array}{llll} B_1^{1l} = 0 & B_1^{1u} = i - a & B_1^{2l} = i + a & B_1^{2u} = 1 \\ B_2^{3l} = 0 & B_2^{3u} = 0 & B_2^{4l} = 1 & B_2^{4u} = 1 \\ B_2^{0l} = i - a & B_2^{0u} = i + a & & \end{array}$$

yielding an average shortest path of $p_i = (i-a)+1-(i+a)+2((i+a)-(i-a)) = 1+2a$. Collecting the results gives

$$c = p^{-1} = \begin{cases} (2 - b)^{-1} & \text{for } i \in [0, a), \\ (2 + a - b - i)^{-1} & \text{for } i \in [a, 1 - a - b], \\ (1 + 2a)^{-1} & \text{for } i \in (1 - a - b, 0.5]. \end{cases}$$

Comparing closeness centrality, we find that agents close to the boundary are less central than agents close to the center of knowledge space ($(2 - b)^{-1} < (1 + 2a)^{-1}$ by the case condition). Furthermore, within the interval $[a, 1 - a - b]$ closeness centrality increases monotonically with i. Thus, given the case condition and auxiliary conditions, agents closer to the center of the knowledge space have higher closeness centrality in the network. Would this result be altered when dropping the auxiliary conditions?

Condition i) $1/2 \leq (a+b)$ ensures relatively low average path lengths in the network, so that the example remains short. Smaller profitable ranges with $1/2 > (a+b)$ do not affect the result. The general argument is that under case 2, agents closer to the center have i) larger neighborhoods and ii) reach further agents more efficiently. (A more detailed argumentation is given in the main text.)

Condition ii) specifies $a \leq b$. As for case 1, this is a necessary condition for obtaining a monotone relationship between an agent's position in technological space and its closeness centrality in the network. For $a > b$ and a, b sufficiently high (e.g. $a = 0.35$ and $b = 0.25$), closeness centrality becomes non-monotonic function of the position in knowledge space between 0 and 0.5. However, firms in the center of knowledge space always have higher closeness centrality than agents at the boundary of knowledge space.

A.2 Clustering Coefficient

This section provides i) formulas for left, right and left-to-right number of triangles depending on the relevant intervals in knowledge space, ii) shows that two statements with respect to the slope of total number of triangles hold, and iii) gives expressions for triangles and clustering depending on the agents position in knowledge space.

Number of triangles In the model, there are three types of connections among an agent i's neighbors (triangles). Neighbors to the left of agent i in knowledge space may connect (left triangles e_i^l), right-hand neighbors of agent i may connect (right triangles e_i^r) and left-hand neighbors may connect to right-hand neighbors of agent i (left-to-right triangles e_i^{lr}). How many triangles of each type form depends on the size of agent i's left and right neighborhood. As agent i's neighborhood is a function of its position in knowledge space, so is agent i's number of triangles. The main text derives in which intervals the different types of triangles increase, decrease, remain stable at zero or remain complete ($1/2(b-a)^2$). The following lists the corresponding formulas derived from the general equations for triangles (equation 2.7). The formulas are needed subsequently to validate statements on the shape of the triangle functions.

Agents $i \leq 1-a-b$ have a complete right neighborhood and therefore complete right triangles. Moving further to the right, the right neighborhood becomes restricted and right triangles as well. When the right neighborhood is smaller a (for $i < 1-2a$), right-hand neighbors do not connect to each other. Applying equation 2.7 for respective intervals yields the number of right triangles,

$$e_i^r = \begin{cases} \frac{1}{2}(b-a)^2 & \text{if } 0 \leq i \leq 1-a-b, \\ \frac{1}{2}(1-2a-i)^2 & \text{if } 1-a-b < i < 1-2a, \\ 0 & \text{if } 1-2a \leq i \leq 1. \end{cases}$$

The situation is symmetric for left triangles. Left neighbors only connect with each other for $i \geq 2a$. Moving further to the right increases the number of left triangles until $i = a + b$, where the left neighborhood becomes complete.

$$e_i^l = \begin{cases} 0 & \text{if } 0 \leq i < 2a, \\ \frac{1}{2}(i-2a)^2 & \text{if } 2a \leq i < a+b, \\ \frac{1}{2}(b-a)^2 & \text{if } a+b \leq i \leq 1. \end{cases}$$

Left-to-right triangles only exist if both neighborhoods exist (if $a \leq i \leq 1-a$). Moving further to the right, left-to-right triangles increase. They attain their maximum of $1/2(b-a)^2$ if the left and right neighborhood contains all agents which connect to the other neighborhood (if $b \leq i \leq 1-b$).

$$e_i^{lr} = \begin{cases} 0 & \text{if } 0 \leq i < a, \\ \frac{1}{2}(i-a)^2 + (b-i)(i-a) & \text{if } a \leq i < b(< 0.5), \\ \frac{1}{2}(b-a)^2 & \text{if } b \leq i \leq 0.5, \end{cases}$$

Given $b > 0.5$, this maximum never is attained. For $i > 1-b$, agent i's right-hand neighbors contributing to left-right clustering are removed as left-hand neighbors are added.

$$e_i^{lr} = \begin{cases} 0 & \text{if } 0 \leq i < a, \\ \frac{1}{2}(i-a)^2 + (b-i)(i-a) & \text{if } a \leq i < 1-b(< 0.5), \\ \frac{1}{2}(1-a-b)^2 + (b-i)(1-a-b) + & \\ (1-i-a)(i-1+b) & \text{if } 1-b \leq i \leq 0.5, \end{cases}$$

Statement 1 *In case 1, $a+(a+b) > 1$, total number of triangles always is increasing or stable with i for $a \leq i \leq 0.5$.*
This is shown by comparing the slopes of the functions for left, right and left-to-right triangles, taking into account the sub-cases $b >\leq 0.5$.
Step 1: The slope of right triangles is

$$\begin{aligned} \frac{\partial e_i^r}{\partial i} &= \frac{\partial 1/2(1-2a-i)^2}{\partial i} \\ &= i + 2a - 1, \quad \text{if } 1-a-b < i < 1-2a, \end{aligned}$$

the slope of left-to-right triangles is

$$\frac{\partial e_i^{lr}}{\partial i} = \begin{cases} b-i & \text{if } a \leq i < b, 1-b, \\ 0 & \text{if } b \leq i \leq 0.5, \\ 1-2i & \text{if } 1-b \leq i \leq 0.5, \end{cases}$$

and the slope of left triangles is

$$\frac{\partial e_i^l}{\partial i} = (i - 2a), \quad \text{if } 2a \leq i < a + b.$$

Step 2: The case condition implies that the initial increase ($a < i < \min(b, 1 - b)$) of left-to-right triangles is larger than the decrease of right triangles, i.e.

$$\begin{aligned} a + (a + b) > 1 &\Leftrightarrow b + 2a - 1 > 0 \\ &\Leftrightarrow (b - i) + (i + 2a - 1) > 0 \\ &\Leftrightarrow \frac{\partial e_i^{lr}}{\partial i} + \frac{\partial e_i^r}{\partial i} > 0. \end{aligned}$$

Step 3: For $\min(b, 1 - b) < i < 0.5$ the cases $b \leq 0.5$ and $b > 0.5$ need to be discussed separately. If $b \leq 0.5$, then from b on left-to-right triangles stagnate at their maximum. However, the case condition ensures that right triangles stagnate at zero before ($b > 1 - 2a$). If $b > 0.5$, the slope of left-to-right triangles eventually becomes $1 - 2i$. This increase is positive for $2a \geq i$ ($(1 - 2i) + (i + 2a - 1) = 2a - i > 0$). For $i > 2a$, left triangles form, which causes an increase of total triangles as well ($(1 - 2i) + (i + 2a - 1) + (1 - 2a) = 1 - i > 0$). Therefore, in case 1, the total number of triangles always increases from a until the center of knowledge space (0.5).

Statement 2 *In case 2, $a + (a + b) < 1$, total number of triangles always is decreasing or stable with i for $1 - a - b < i \leq 0.5$.*
To proof this, it suffices to show that the decrease of right triangles always outweighs the increase of the sum of left-to-right and left triangles. The first step is to note that, for $1 - a - b < i \leq 0.5$, whenever left-to-right triangles or left triangles increase, right triangles decrease. This implies that the sum over the slopes of all three triangle types is above or equal to the slope of total triangles, without the need to consider the different case conditions. Therefore, in the final step, it suffices to show that the sum over the slopes of all three triangle types always is negative or zero.
Step 1: Right triangles decrease for $1 - a - b < i \leq 1 - 2a$. $1 - 2a$ is only below 0.5 if $a > 1/4$. However, $a > 1/4$ implies that left triangles do not increase for $1 - a - b < i < 0.5$. Furthermore, for $1 - 2a \leq i$, left-to-right triangles already attained their maximum, because the case condition implies that $b < 1 - 2a \leq i$. Therefore, right triangles always decrease when left or left-to-right triangles increase.
Step 2: For summing up all three types of triangles, the two cases for b need to be distinguished. First, assume that $b \leq 0.5$, then the maximum slope possibly attained is

$$\frac{\partial e_i^{lr}}{\partial i} + \frac{\partial e_i^l}{\partial i} + \frac{\partial e_i^r}{\partial i} = (b - i) + (i - 2a) + (i + 2a - 1) = i - 1 + b \leq 0,$$

because $i \leq 0.5$ and $b \leq 0.5$. Assuming $b > 0.5$ gives a total slope of

$$\frac{\partial e_i^{lr}}{\partial i} + \frac{\partial e_i^{l}}{\partial i} + \frac{\partial e_i^{r}}{\partial i} = (i + 2a - 1) + (i - 2a) + (i + 2a - 1) = 0.$$

Therefore, the sum over the slopes of all types of triangles always is negative or zero.

Taking into account the result of step 1, the result of step 2 implies that in case 2, $a + (a + b) < 1$, total number of triangles always is decreasing or stable with i for $1 - a - b < i \leq 0.5$

Two cases The interest is in triangles and clustering as functions of the agents position in knowledge space. More specifically, we are interested in which slopes (positive or negative) these functions take in the different intervals for case 1 and 2. The slope of the triangle function is clear from the case condition and the two above statements. Recall that in case 1 (case 2), triangles first are stable for $0 \leq i < 1 - a - b$ (for $0 \leq i < a$), then decrease (increase) for $1 - a - b \leq i < a$ ($a \leq i < 1 - a - b$) and later increase (decrease) again or remain stable until the center of knowledge space. Normalizing triangles by the potential number of triangles (1/2 degree^2) yields the clustering coefficient. In case 1 (case 2), triangles and degree are both decreasing (increasing) with i for $1 - a - b \leq i < a$ (for $a \leq i < 1 - a - b$). Therefore, it remains to show for case 1 (case 2) that clustering is decreasing (increasing) as well in this interval.

First consider **case 1** with $a > 1 - a - b$. Agents $i \in [1 - a - b, a)$ have a right neighborhood only and, therefore, the number of right triangles equals the total number of triangles ($e_i^r = e_i$). The agents in this interval obtain different clustering coefficients depending on the parameter value a. Given $a \leq 1/3$, all agents i have right-hand neighbors which contribute to clustering. In this case, the relevant boundaries are

$$B_i^{1l} = 0 \qquad B_i^{1u} = 0 \qquad B_i^{2l} = i + a \qquad B_i^{2u} = 1 \qquad B_j^{2l} = j + a$$

and $\max(B_i^{2u} - a, B_i^{2l}) = 1 - a$. Inserting the boundaries gives

$$e_i = e_i^r = \int_{i+a}^{1-a} 1 - (j + a)\,\mathrm{d}j = \frac{1}{2}(1 - 2a - i)^2$$

Given $a \geq 1/3$ agents $i < 1 - 2a$ and agents $i \geq 1 - 2a$ are going to have different clustering coefficients. For agents $i \in (1 - a - b, 1 - 2a)$, the total number of triangles e_i equals the formula above ($e_i = 1/2(1 - 2a - i)^2)$). However, right-hand neighbors of agents $i \in [1 - 2a, a)$ have an empty right-hand neighborhood and therefore clustering to the right is zero. We summarize this result and write

$$e_i = \begin{cases} \frac{1}{2}(1-2a-i)^2 & \text{if } i \in [1-a-b, a) \wedge a \le 1/3, \\ \frac{1}{2}(1-2a-i)^2 & \text{if } i \in [1-a-b, 1-2a) \wedge a > 1/3, \\ 0 & \text{if } i \in [1-2a, a) \wedge a > 1/3. \end{cases}$$

Note that the number of triangles is decreasing or constant with i. Taking into account the degree of $1-a-i$, the clustering coefficient becomes

$$c_i = \begin{cases} \left(\frac{1-2a-i}{1-a-i}\right)^2 & \text{if } i \in [1-a-b, a) \wedge a \le 1/3, \\ \left(\frac{1-2a-i}{1-a-i}\right)^2 & \text{if } i \in [1-a-b, 1-2a) \wedge a > 1/3, \\ 0 & \text{if } i \in [1-2a, a) \wedge a > 1/3. \end{cases}$$

The derivations with respect to i are

$$\frac{\partial c_i}{\partial i} = \begin{cases} 2\frac{1-2a-i}{1-a-i}\frac{-a}{(1-a-i)^2} < 0 & \text{if } i \in [1-a-b, a) \wedge a \le 1/3, \\ 2\frac{1-2a-i}{1-a-i}\frac{-a}{(1-a-i)^2} < 0 & \text{if } i \in [1-a-b, 1-2a) \wedge a > 1/3, \\ 0 & \text{if } i \in [1-2a, a) \wedge a > 1/3. \end{cases}$$

Derivations are negative as the first fraction is positive (by $i < 1-2a$ and $0 < 1-a-b < 1-a-i$) and the second fraction is negative (by $a > 0$). Therefore, both the number of triangles as well as the clustering coefficient are decreasing with i.

Now consider **case 2** with $a < 1-a-b$. Agents $i \in [a, 1-a-b)$ have a complete right neighborhood and a restricted left neighborhood with the boundaries

$$B_i^{1l} = 0, \qquad B_i^{1u} = i-a, \qquad B_i^{2l} = i+a, \qquad B_i^{2u} = i+a+b.$$

With this neighborhood, left, right and left-to-right triangles become respectively

$$\begin{aligned} e_i^l &= \begin{cases} \frac{1}{2}(i-2a)^2 & \text{if } i > 2a, \\ 0 & \text{else,} \end{cases} \\ e_i^r &= \frac{1}{2}(b-a)^2, \\ e_i^{lr} &= \begin{cases} \frac{1}{2}(b-a)^2 & \text{if } i \ge b, \\ \frac{1}{2}(i-a)^2 + (b-i)(i-a) & \text{else.} \end{cases} \end{aligned}$$

Note that the left-to-right triangle case $i \geq 1-b$ is excluded as $i < 1-a-b \Rightarrow i < 1-b$. The total mass of links among neighbors $e_i = e_i^l + e_i^r + e_i^{lr}$ is clearly increasing because both e_i^l and e_i^{lr} are increasing/stable and e_i^r remains stable. The clustering coefficient is obtained by normalizing the mass of links by $1/2d_i^2 = 1/2(i-a+b)^2$.

$$c_i^l = \begin{cases} \left(\frac{i-2a}{i-a+b}\right)^2 & \text{if } i > 2a, \\ 0 & \text{else,} \end{cases}$$

$$c_i^r = \left(\frac{b-a}{i-a+b}\right)^2,$$

$$c_i^{lr} = \begin{cases} \left(\frac{b-a}{i-a+b}\right)^2 & \text{if } i \geq b, \\ \left(\frac{i-a}{i-a+b}\right)^2 + \frac{2(b-i)(i-a)}{(i-a+b)^2} & \text{else.} \end{cases}$$

In order to see how the clustering coefficient changes with i, we take the derivative with respect to i:

$$\partial c_i^l/\partial i = \begin{cases} \frac{2(i-2a)(a+b)}{(i-a+b)^3} > 0 & \text{if } i > 2a, \\ 0 & \text{else,} \end{cases}$$

$$\partial c_i^r/\partial i = \frac{-2(b-a)^2}{(i-a+b)^3} < 0,$$

$$\partial c_i^{lr}/\partial i = \begin{cases} \frac{-2(b-a)^2}{(i-a+b)^3} < 0 & \text{if } i \geq b, \\ \frac{2(b-i)}{(i-a+b)^2} - \frac{2(i-a)^2+4(b-i)(i-a)}{(i-a+b)^3} >< 0 & \text{else.} \end{cases}$$

The left-hand contribution to clustering is always increasing or stable. The clustering contribution to the right is always decreasing because the size of the overall neighborhood increases whereas the mass of links among right-hand neighbors remains constant. Finally, the clustering contribution by links between left- and right-hand neighbors at the beginning increases ($i = a$) and eventually decreases. The turning point depends on the parameters a and b. Overall clustering, that is the sum of the three types of clustering is a concave function which obtains its maximum for $i < 2a$ and $i \leq b$ with $i = \frac{3ab-2a^2}{2b-a}$. For $1-a-b$ close to a the maximum might be obtained at the boundary $(1-a-b)$.

CHAPTER 3

Technological Effects on Network Formation

3.1 Introduction

This chapter investigates the technological-distance effect on network formation empirically. Our theoretical model in the previous chapter assumes that firms are positioned in technological space and a firm-pair forms a research alliance depending on its technological distance. The alliance decisions of all firm-pairs create a research network. In the model, the network structure depends on which technological distances are profitable and the position of a firm in this network becomes a function of its position in technological space.

The empirical application is on the pharmaceutical industry because the model is expected to be especially relevant for this industry. Firstly, the alliance network in the industry is large and half of the alliances focus on joint research & development. Secondly, firms possess distinctive technological competences. Both can be traced back to the biotechnology revolution (Arora and Gambardella, 1990; Galambos and Sturchio, 1998; Henderson et al., 1999; Orsenigo et al., 2001). Although today all pharmaceutical firms are based on modern life sciences (Cockburn et al., 1999), research alliances remain important. No firm is able to master all the fields that are potentially relevant for the development of new drugs. Therefore firms need to specialize and when necessary join complementary technological knowledge in research alliances (Powell et al., 2005). This makes the pharmaceutical industry a promising candidate for an empirical application. A further attraction is that the measurement of the firms' technological knowledge with patent data seems valid. In this industry, patents are highly used (Arundel and Kabla, 1998) in order to protect intellectual property and to signal technological competence (Bureth et al., 2007).

We sample a network which consists of 200 firms and their 300 research alliances formed within a six-year period. The analysis proceeds at three levels: i) at the dyad level, we use pairwise distances and the presence or absence of an alliance between pairs to estimate the benefit-distance relationship. Using this estimate of the distance-benefit function we can predict (probabilistically) ii) individual firms' ego-network properties, and iii) the network structures. The results confirm the relevance of the benefit-distance relationship as instrumental in pairwise alliance formation which in turn influences higher-level network structures. In addition, the analysis highlights the size of the firm's patent portfolio as a determinant of alliance formation and higher-level network structures. We conclude that the technological position of the firm is best captured by considering the size dimension (the patent portfolio size) jointly with the structural dimension (the benefit-distance effect).

The chapter is structured as follows: the next section discusses related empirical work on alliance and network formation. Section 3.3 develops the hypotheses. Empirical methods and statistical evidence are presented in section 3.4. Section 3.5 gives the results and investigates their sensitivity to alternative measures of technological distance. The chapter ends with a discussion and conclusion.

3.2 Background

3.2.1 Research Alliances in the Pharmaceutical Industry

An alliance in the pharmaceutical industry may govern any of the activities along the value chain. Our CGCP data set, described in the sample section 3.4.1, provides a categorization according to the main purpose of the alliance. Roughly, we observe marketing and distribution alliances (25%), pure licensing and contract research (25%), manufacturing and supply (10%) and joint research and development alliances (50%). Many alliances include agreements on subsequent stages of the product life cycle. For example, research and development agreements are often combined with allocation of commercialization rights in case of success. Furthermore, alliances might involve equity transfers between the partnering firms.

In this chapter, we focus on joint research alliances where we expect the strongest effect of technological distance on alliance formation. We define research alliances as long-term agreements for reciprocal technology sharing and joint undertaking of research between independent actors. This includes research joint ventures in which two companies found a distinct firm for joint research; as well as research collaborations which establish joint undertaking of R&D projects with shared resources (definition from Hagedoorn and Schakenraad, 1994).

Pharmaceutical companies frequently enter research alliances. More than 700 alliances are formed annually, with a total value of over 30 billion US dollars in 2004 (recap, cited in Gassmann, 2008, p.75). The relevance of research alliances has increased continually in the last years, both in terms of the number of alliances and in terms of amounts spent (in total and in percent of the R&D budget) (Gassmann, 2008; Ernst&Young, 2008, p.75,p.47 resp.). Most research alliances are formed between integrated pharmaceutical companies and small biotechnology firms. Pharmaceutical companies spend a considerable part of their overall R&D budget in research alliances, for example Aventis engages with 15% of its R&D budget (Gassmann, 2008, p.75). Biotechnology firms finance the lion share of their R&D expenditures this way (Ernst&Young, 2007, p.17).

Motives for research alliances may stem from efficiency considerations or firm interdependencies. Efficiency is enhanced, for example, due to the realization of economies of scale and scope, cost and risk sharing, easier access to finance, speed to market, internalization of knowledge spillovers, and more effective use of extant resources (see e.g. Hagedoorn, 1993; Hemphill and Vonortas, 2003). Firm interdependencies arise when two firms occupy similar positions in the industry (competitive interdependence) or when firm activities are closely connected (symbiotic interdependence) (Pfeffer and Nowak, 1976). Firms with competitive interdependence might ally in order to mitigate competition for the input and sales markets (Burt, 1980; Eisenhardt and Schoonhoven, 1996; Pfeffer and Nowak, 1976). Symbiotic interdependence is emphasized in the resource based view of the firm and arises when the activity of one firm depends on the activity or the resources of another firm (Richardson, 1972). Here, alliances enable close coordination of activities or access to complementary external resources.

In the pharmaceutical industry, symbiotic interdependence is likely to be especially high. Since the 1980s, the biotechnological revolution brought a whole array of new scientific disciplines to the life sciences (Galambos and Sturchio, 1998). Because the scientific advances originated in universities and public research organizations outside the established pharmaceutical companies, the technological change induced industrial change. New biotechnology firms entered the industry in several waves, endowed with specific research approaches and tools (Orsenigo et al., 2001). Although the new scientific approaches diffused and nowadays all firms apply modern life sciences in their research, technological knowledge remains fragmented and dispersed among firms (Cockburn et al., 1999). It remains a common theme that not even the largest firm is able to do all the research for tomorrow's products in-house (Ernst&Young, 2008). Therefore, access to complementary technological knowledge is one of the main motives to engage in research alliances (Hagedoorn, 1993; Herrling, 1998).

The motivation to form an alliance is closely connected to the search for relevant partners. Given that a firm needs to access complementary technological knowledge, then this firm is going to consider how the technological knowledge of its potential partners fit its own technologies. One of the hypotheses put forward in this chapter is that two firms having an intermediate technological distance are most likely to form a research alliance. Roughly speaking, the argument is that two firms engaging in joint research seek new technological knowledge but need some technological overlap to work together (see discussion in chapter 2, section 2.2).

3.2.2 Empirical Studies on Research Alliance Formation

The question how the technological endowment of two firms affect their propensity to form a (research) alliance has been seen in some prior empirical research (Cantwell and Colombo, 2000; Mowery et al., 1998; Rothaermel and Boeker, 2008; Stuart, 1998). The work of Mowery et al. (1998) seems to be the earliest effort in this direction. As in our work, it argues that absorptive capacity and novelty gain yield a trade-off in partner choice and tests for the inverse-U-shaped benefit-distance effect. Different from our work, their analysis considers research joint ventures in various industries. In their study, technological distance between firm-pairs is measured with cross and common patent citation rates. Estimation of the effect of technological distance on joint venture formation is accomplished with a logit regression on a pooled matched-pair sample. The findings support a curvilinear benefit-distance effect; albeit with a strong preference for technological similarity.

Cantwell and Colombo (2000) investigate the formation of different types of alliances among the 68 largest firms of the IT sector. They argue that firm-pairs with smaller technological distance have more complementary technologies as well as higher absorptive capacity and, therefore, are more susceptible to engage in close interaction for joint knowledge creation and learning. On the other hand, firm-pairs with distinct technologies but similar products are likely to interact in more market-like transactions such as licensing. Two measures of technological similarity are provided. The first indicates whether two firms are both active in one of three broad technological niches. As alternative measure of technological distance, correlated revealed technological advantage (cRTA) is calculated on the firm-pair's patents.[1] Results of difference-of-means tests using both measures support the hypothesis that alliances in general and technological agreements in particular are more frequent for technologically close firms. A further finding is that technological similarity, measured by cRTA, is not positively associated with all kinds of technological agreements. Whereas technological similarity increases the probability of licensing and non-equity technological alliances, it decreases slightly the probability of research joint ventures. This finding is opposite to the results of (Mowery et al., 1998) who focused exclusively on research joint ventures and found that technological similarity increases the probability of occurrence. The explanation put forward by Cantwell and Colombo (2000) is that equity joint ventures are more efficient for inter-organizational learning when the knowledge bases of the partners differ.

[1] A firm's revealed technological advantage (RTA) indicates, for a vector of technological fields, the extent to which a firm is specialized in a given technological field relative to the population's average specialization. The cRTA is the correlation coefficient of the RTA vectors of two firms. (For mathematical expressions, see appendix B.2 where cRTA is applied in the sensitivity analysis.)

In our view, a further explanation might be differences of the population (IT versus any industry) and different measures of technological similarity (cross and common citation rates versus cRTA).

With respect to our work, adverse effects of equity joint ventures should not be expected because our sample includes only a small share of research joint ventures; around 2% of all research alliances. However, alternative measures of technological similarity might yield different results and therefore will be presented in the sensitivity analysis.

The study of Rothaermel and Boeker (2008) considers alliance formation in the pharmaceutical industry. Their sample consists of pharmaceutical-biotechnology firm-pairs built by crossing about 60 pharmaceutical with 500 biotechnology firms. Observations are over a four year period. The reasoning, again, draws from the symbiotic interdependence argument of the resource-based view of the firm and the inter-organizational learning perspective. Whereas alliances are motivated by complementarities between firms with different competences, alliances are more efficient for firms having a similar knowledge base. In addition, based on reputation arguments, the authors consider moderating effects of the biotechnology firm's age. From all the results of the study, contradictory results on the effect of technological similarity on the propensity of alliance formation are especially interesting in our context. Technological similarity is measured by common and cross patent citation rates, as in Mowery et al. (1998). However, the logit regression yields a negative effect of common citation rate and a positive effect of cross citation rate on alliance formation, both at a 5% significance level. The explanation of the authors is that common citation rate may be a better proxy of technological similarity than cross citation rate. A negative effect of common citation rate might arise because firms are too similar to complement each other (Rothaermel and Boeker, 2008, p.73).

Our own experience with these measures in an exploratory analysis on an uncleaned data set suggests that there are also technical issues to consider. In the study of (Rothaermel and Boeker, 2008), crossing of firms yields about 30000 firm-pairs which cited each others patents 750 times (cross citation rate) and the same patents 5460 times (common citation rate) (Rothaermel and Boeker, 2008, p.59). This implies that most firm-pairs do not cite each other patents or the same patents and, therefore, technological similarity becomes zero for these firm-pairs. Thus, in the sample the distance measures applied are largely uninformative.[2] Yet, both measures of technological similarity are significant with opposed signs. The reason might be in the estimation procedure, in which the common logit model is regressed on a large sample of firm-pairs. The sample of firm-pairs results from pairing each firm with all other

[2]This observation led us not to engage in building a data set for calculation of common and cross citation rates. In the study of (Mowery et al., 1998) the cross citation rate is ten times higher whereas the common citation rate is on about the same level as in (Rothaermel and Boeker, 2008).

firms. The 60 pharmaceutical firms and 500 biotechnology firms result in 30000 firm-pairs. Firm-pair observations are not independent over firms because each firm enters many observations. If this is not taken into account in the estimation, either through correction terms or by explicitly modeling dependencies among observations, significance levels might be underestimated (too low) (see e.g. Fafchamps and Gubert, 2007; Hoff, 2003). The conclusion from this study is largely technical. Firstly, measures of technological similarity based on patent citations might be misleading. Secondly, deflation of standard errors due to crossing of firms is an issue.

Stuart (1998) takes a structuralist perspective. Building on the argument of White (1981) that a firm's action in a market is determined by the position the firm takes relative to other firms in the market, Stuart (1998) claims that alliance formation is determined by the position the firm takes in technological space. He argues that for reasons of opportunity, absorptive capacity, and efficiency firms in crowded regions of technological space are more likely to form alliances. In addition, firms located in isolated regions might seek alliances with firms in crowded regions because crowded regions are likely to represent the industry's core activities. The implication is that technological space structures alliance formation by the distribution of firms therein. The theoretical model in the previous chapter in principle takes the same stand-point by ascribing a structuring role to technological space. However, in our model, firms are uniformly distributed in technological space and the structuring element is the benefit-distance effect on a firm-pair. Because we do not deny that firms in reality are unevenly distributed in knowledge space, our model should not be understood as an alternative explanation but rather as a refinement. According to Stuart, firms in densely populated regions are positioned in a rich local environment which provides many opportunities for alliances. Our model adds that this is actually only the case if technological similarity is preferred. Given that technological distance is beneficial to alliance formation, it is not the local environment in technological space but more distant, possibly sparsely populated, regions which determine the opportunities of the firm.

A methodological difference however remains. The starting point of Stuart is that the decision to form an alliance is determined by the overall structure provided by the population of firms in technological space. In a second step, he proposes that this kind of decision making is going to be visible in the alliance formation between firm-pairs. We argue the opposite way round. In our theoretical model, alliance formation is exclusively determined by cost-benefit considerations of the firm-pair and we argue that this is going to be visible in the firm network position.

In the empirical analysis, Stuart (1998) tests the implications of his arguments on a longitudinal sample of semiconductor firms. Regressions are at the firm and the dyad level. At the firm level, a Poisson regression estimates the effect of the firm's position in technological space on its alliance formation rate. At the dyad level, a Probit regression estimates the effect of a firm-pair's technological distance on alliance formation. The finding is that two firms which are technologically close are more likely to form an alliance and that firms which are positioned in a crowded region have more alliances. A finding which is internally consistent with Stuart's arguments as well as with our theoretical model.

3.2.3 Empirical Studies on Research Network Formation

In the theoretical model, which we attempt to test in this chapter, firm-pairs form alliances and thereby create a network. The analysis in chapter 2, section 2.4, discusses the implication of the dyadic decision making on higher-level network structures, i.e. the firm position in the research network and the global network structure. Therefore it is noteworthy that all the studies discussed above remain on the dyad level, the only exception being (Stuart, 1998). Furthermore, when searching the literature, we did not find further empirical contributions about how the position of a firm in technological space affects the firm's position in the network of alliances. Related empirical work rather investigates the effect of the firm's technological competence (e.g. number of patents) on the firm's rate of alliance formation (Ahuja, 2000; Eisenhardt and Schoonhoven, 1996; Shan et al., 1994; Zhang et al., 2007).

Two studies find positive and significant effects of the firm's technological competence on the formation rate of technological alliances in the chemicals and semiconductor industry respectively (Ahuja, 2000; Eisenhardt and Schoonhoven, 1996).[3] Shan et al. (1994) analyze the relationship of alliance formation and innovative capabilities for young biotechnology firms in the pharmaceutical industry. They do not find that the number of the firm's patents affects the number of its commercial alliances. However, an important qualification may be that the study is on alliance formation during the 1980s; a very early period. The more recent work of Zhang et al. (2007) considers the alliance activity of 43 large pharmaceutical firms over the period 1993-2002. Influenced by the learning-organization perspective, they argue that a firm with a broad knowledge base has many opportunities to access and to commercially exploit the technological knowledge of other firms. Breadth of knowledge is measured in terms of the number of technological fields in which the firm patented and is found to increase the rate of alliance formation.

The study of Gay and Dousset (2005) explicitly links the firm's technological competence to its position in the network of alliances. This work provides a descriptive analysis of the alliance network in the human antibody sector, a sub-sector of the pharmaceutical industry. It is convincingly shown that firms holding intellectual property on 'key' innovations obtained central positions in the network. By out-licensing their innovations, these actors became hubs with high out-degree, betweenness and closeness

[3] The focus of these studies is the relationship between technological and social effects on alliance formation. We treat this question in the next chapter, 4, which provides a more detailed discussion in section 4.2.

centrality. The formation of hubs is found to induce network structures characterized by short average path length and higher clustering.

The findings of Gay and Dousset (2005) exemplify the findings of a study on the formation of the overall pharmaceutical network (Orsenigo et al., 2001). Orsenigo et al. (2001) describe how waves of entries of biotechnology firms altered the structure of the alliance network in the pharmaceutical industry. On the one hand, entry of firms with general purpose technologies decrease the hierarchy in the network because these technologies are widely applicable. On the other hand, entry of firms with co-specialized technologies increase the hierarchy in the network. Thus, the study of Orsenigo et al. (2001) focus on how the entry of firm types influence network structures. Our approach is more micro-oriented as we investigate how the alliance decisions of firm-pairs influences network structures.

3.2.4 Summary

We may summarize our discussion of prior empirical work as follows. Firstly, the inverse-U-shaped technological distance effect on alliance formation has been found to be relevant for the formation of research joint ventures (Mowery et al., 1998). Secondly, all studies on alliance formation found that technologically close firm-pairs are more likely to enter a research alliance than technologically distant firm-pairs. Thirdly, technical issues to consider include dyadic interdependence and alternative measures of technological distance. Fourthly, technological competence, as measured for example by the size of the firm's patent portfolio, is found to be positively related to the firm's rate of research alliance formation. To the best of our knowledge, the question of how the benefit-distance effect influences higher-level network structures has not yet been treated empirically. Guided by the theoretical model of the previous chapter, the following analysis focuses on this issue.

3.3 Hypotheses

The main implication of the model is that when the distance benefit range is small (large) relative to the technological space, a firm which is central in the technological space, is more (less) central in the research network. An obvious way to proceed would be to determine the relevant case for a population of firms and test the implication of the model directly. To this end, one needs to measure the distance benefit range, the diameter of the knowledge space and how central a firm is in knowledge space.

However, whereas in the model firms are uniformly distributed in a one-dimensional space, in reality we are confronted with unevenly distributed firms in a multi-dimensional space. In such a setting, two firms which are positioned in different regions of technological space but have the same distance to the center of technological space do not necessarily have the same opportunities to form alliances. The firm's actual opportunities to form alliances depend on its distances to all other firms in knowledge space. This means that in our empirical setting we lose information if the position of a firm is indicated only by its distance to the center of technological space. A firm's position in technological space is better expressed by its technological distance to all other firms.

Therefore, we do not test directly the relationship between central positions in technological space and firm network positions as well as global network structures, though we will provide some visual evidence that is indicative. We do, however, derive three hypotheses: the first is in fact the key assumption of the model, which is the distance-benefit relationship on the dyad level. The second hypothesis treats its implications on the network characteristics on the firm level. Finally, the third hypothesis addresses the implications on network measure distributions on the global level. In this way, the assumption on the benefit-distance range is disentangled from its effect on higher-level network structures.

The first hypothesis is simply the main assumption of the model:

Hypothesis 1 ***Alliance formation.*** *The probability of two firms forming an alliance will be a curvilinear function, having an internal maximum, of their technological distance.*

The theoretical model assumes that the benefit-distance relationship is the same for all firm-pairs. Therefore, the position of a firm in the network depends on its position in knowledge space:

Hypothesis 2 ***Ego-network structures.*** *Firm-level network characteristics depend on the firms' position in the knowledge space for a given benefit-distance relationship.*

On the network level, network measures describe the architecture of a network by neglecting the individuality of the nodes. The analysis showed that depending on the distance-benefit effect network measure distributions will be more or less skewed and on a higher or lower level. The relevance of the model for the network architecture is tested by the following hypothesis:

Hypothesis 3 ***Global network structures.*** *Distributions of network measures are related to the firms' distribution in knowledge space for a given benefit-distance relationship.*

The hypotheses are formulated in broad terms to capture the main idea of the model: the benefit-distance relationship is a local effect, which determines the alliance decision of firm-pairs. Because the network is the aggregate of all alliance decisions, the local effect shapes firm network characteristics and network measure distributions.

3.4 Empirical Methods

3.4.1 Sample

The firm sample is drawn from the CGCP database. The CGCP database is a comprehensive collection of publicly announced formal agreements. A valuable feature is that it classifies alliances by industry and type (such as e.g. joint venture, commercial or research alliance).[4] The classification allows us to focus on research and development alliances in the pharmaceutical industry.

The sample consists of the 250 firms, being most active in the pharmaceutical industry. To derive the sample, first all dyadic (bio-)pharmaceutical alliances between the years 2001 and 2006 (inclusive) have been extracted. Because firm-level information needs to be added, not all firms involved could enter the sample. Selecting the 250 most active firms assured that the network will be reasonably dense, with many alliances among the selected firms.

This sample is not representative; neither of the pharmaceutical industry nor of the global pharmaceutical network. However, the dependent variable is the alliance decision of the firm-dyad and not the number of alliances of the firm. Because selection is not based on the dependent variable, estimates need not be biased.

The technological position of firms is measured with patent data. The advantages and disadvantages of measuring technological capabilities with patent data have been discussed elsewhere (e.g. Pavitt, 1982). Because in the pharmaceutical industry firms patent extensively (Arundel and Kabla, 1998), we think that patent information reflects sufficiently the technological activity of the firms. The objectivity, information content and availability of patent data makes it superior to other information sources in our case.

The patent data have been extracted from the EPO Patstat database (EPO, 2008). Only those patents, which seem relevant for the bio-pharmaceutical industry, have been considered. The restriction is based on concordances of the international patent classification (IPC) on the four digit level to the biopharmaceutical industry. In detail, the set of IPC classes considered comprises those of the OECD definition (OECD, 2008b), the MERIT definition (Verspagen et al., 1994) and the ISI definition (Schmoch et al., 2003). One invention is often patented via a priority application to a national office and equivalent foreign versions of the application. In these cases, double counting has been avoided by considering only the priority application (OECD, 1994).

The hypotheses imply a direction of causality, namely that a firm's technological characteristics affects its alliance activity. This is accounted for by sampling the patent data from a time period previous to the time period of the alliance data. Whereas the alliances took place between the years 2001 and 2006, the patents have a priority date between the years 1995 and 2000.

[4] For a description see www.cgcpmaps.com .

The firm names given in the alliance database denote mostly a pharmaceutical business, either the entire group or a subsidiary. Therefore patents have been matched on the same level when possible. In those cases where the pharmaceutical business is part of a diversified group but applies for patents solely in the name of the group no matching can be done. Additionally, for some firms no patents have been found due to the time or IPC restriction.

The patent matching yielded patent applications within the given priority date and IPC classes for 212 firms or their respective pharmaceutical business. For ten firms, mostly software and service firms, no patents could be found at all. Six firms only applied for patents on behalf of a diversified group. Twenty-two firms applied for patents but after the given time period.

In order to control for firm size, the number of employees has been collected from publicly available information, mostly annual reports of the SEC. About seventy per cent of the figures are at or before 2001. For the rest of firms this information could only be obtained from later years. For 14 out of the 250 firms, the number of employees could not be found.

Thus, of the initial 250 firms, 38 have zero or missing patent assignments, 14 have missing employee information and 45 firms have either no patent or no employee information assigned. Finally, for 205 firms, which is 82 percent of the sample, patenting and employee information is given, and these firms constitute the sample we work with.

3.4.2 Measures

Joint technological agreement

The dependent variable at the dyad level, joint technological agreement (*jointtech*), is defined as a joint project of two firms, in which both firms contribute to research and/or development. This definition excludes for example research projects conducted by one firm and financed by another. The fact that only publicly announced agreements enter the CGCP data base inevitably imposes a restriction to formal agreements.

Firm network position and network structure

The dependent variable at the firm level is the firm network position. At the network level it is the network structure. The firm network position as well as the network structure are described using the four network measures degree centrality, closeness centrality, clustering coefficient and the number of triangles a firm is involved in. (Short notations are “degree”, “closeness”, “clustering” and “triangles” respectively. For definitions see chapter 2, section 2.4). All network measures are calculated from the network of joint technological agreements among the firms, for which the distance-benefit relationship is estimated.

Technological position

The technological position of a firm is given by its technological distance to all other firms. The technological distance between any two firms is measured on their patent portfolios, where we take into account the size of the patent portfolios as well as the technological classes covered by the portfolio.

During examination, a patent examiner of the patent office assigns each patent according to the inventions claimed to one or several technological classes of the international patent classification (IPC) (OECD, 1994, p.30). Therefore, the IPC classes of a firm's patents reveal in which technological fields a firm is active. For indication, we use the main and secondary IPC classes. Intuitively, two firms are technologically close when they patent in the same technological fields. To capture this we use "overlap", defined as the number of IPC classes covered jointly by both firms divided by the number of IPC classes covered by at least one firm:

$$overlap_{ij} = \frac{|IPC_i \bigcap IPC_j|}{|IPC_i \bigcup IPC_j|},$$

where IPC_i is the set of IPC, in which firm i had at least one patent application and $||$ denotes the size of the set. In order to allow for a curvilinear relationship the square of the overlap ($overlap_{ij}^2$) is included in the estimations as well.

The overlap measure loses information on the size of the patent portfolios. Therefore, additional information on the size of the patent portfolios of firms i and j is captured by two further variables: the sum and the absolute difference of the log-transformed patent count of firm i and j ($absDiffLnPC_{ij}$ and $sumLnPC_{ij}$). These measure whether the potential partners are jointly large, in terms of patent holdings; and whether they differ in size.

Note that $absDiffLnPC_{ij}$ and $sumLnPC_{ij}$ are information equivalent to the log transformed patent counts of the two portfolios. The number of patents is log-scaled in order to take into account the decreasing importance of one more patent in a bigger patent portfolio. Technically, the log-scale leads to less skewed distributions.

In the literature other distance measures based on patents have been used. (Mowery et al., 1998; Schoenmakers and Duysters, 2006) calculated the overlap of patent citations. Other measures include the cosine index (Jaffe, 1986, 1989), the correlated revealed technological advantage (cRTA) (Cantwell and Colombo, 2000; Gilsing et al., 2008; Nooteboom et al., 2007) or the euclidean distance (Rosenkopf and Almeida, 2003). Some of these will be considered in the sensitivity analysis in Section 3.5.2 below.

Firm size

Features of drug development and commercialization hint to further drivers of alliance formation (Galambos and Sturchio, 1998; OECD, 2008a). Development of new drugs is extremely costly and time consuming. On average, 800 million dollars need to be spent over 10 years in order to bring a new drug to the market (DiMasi et al., 2003). Drug application processes are country-specific and demand strong organizational competencies to meet legal requirements. Because production costs are low compared to the high initial development expenses, sales revenues need to be maximized. This can only be achieved with strong marketing and distribution channels in national markets.

Because the size of the patent portfolio is strongly correlated with the size of the firm, controlling for firm size is crucial to sort out technological from financial and organizational interdependencies. This is achieved by introducing the two variables $absDiffLnEmployees_{ij}$ and $sumLnEmployees_{ij}$ combining the size information of two firms i and j. Similarly to our treatment of the size of the patent portfolios, they denote the sum as well as the absolute difference of the log-transformed number of employees of two firms i and j.

3.4.3 Statistical Analysis

In the following, we provide statistics which correspond to the three hypotheses on i) alliance formation, ii) ego-network structures and iii) global network structures. A summary is provided at the end of the statistical analysis.

Alliance formation. The basic assumption of the model is that the decision of two firms forming an alliance depends on their technological distance. Specifically, the relationship between the benefit of forming an alliance and technological distance is assumed to be inverse-U-shaped. Therefore, we provide first descriptive statistics on the benefit-distance relationship. In addition, basic information on further regressors on alliance formation is given.

In our sample, there are in total 205 firms for which patent and size information is given. Crossing all firms yields 20910 firm-pairs. These firm-pairs effected 339 technological agreements, corresponding to 2% of all potential links. Firms contributed unequally to link formation in the observed network. Whereas 39 firms have no links with other firms in the sample and 41 firms have one link only, five firms have fourteen or more links within the network. Overlap, our measure of technological proximity, on average is 0.3 with a variance of 0.05. It is slightly right skewed (0.4) with 11.1% of dyads having no overlap and 0.2% having complete overlap. Since overlap is mostly an internal point of the unit interval, it is a measure, which is capable of differentiating the firm-pair distances.

The box-plot in figure 3.1 compares the overlap of firm-pairs forming and not forming an alliance. The first quartile (the lower end of the box) and the median (the bar in the box) of overlap is higher for firm-pairs forming an alliance. This suggests that technological proximity is preferable, which corresponds to a small maximum profitable distance, $a + b$, in the theoretical model.

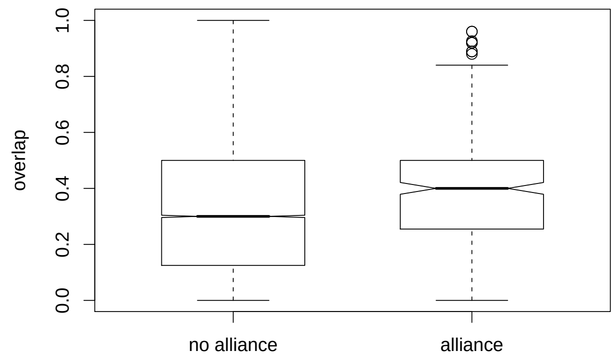

Figure 3.1: *Box-plot of technological proximity (overlap) depending on alliance formation (jointtech). The boxes comprise the lower and upper quartile of respective distributions, the median is marked with a bar, hinges extend the boxes by at most 1.5 the interquartile range, notches indicate 95% confidence intervals around the median assuming independently, normally distributed data.*

The patent and employee information is used to construct further regressors describing the dyad. The distribution of number of patents is extremely right skewed, as is the number of employees. Number of patents range from one patent for eleven firms to 10500 patents for one firm, with a median of 62 and a mean of 591. The distribution becomes symmetric in log-scale with median being 4.2 and mean 4.3. Sizes of the firms ranges from 5 to 120000. Again, log-transformation centers the distribution around a value of 6. Because the number of patents and the number of employees have been log-scaled before being summed and differenced, the resulting variables all have a smooth distribution ranging between 0 and 30.

Table 1 shows that all variables are significantly correlated. The high significance is partly the effect of inflating the observations by forming firm-dyads.[5] Nevertheless, all technological indicators are highly correlated with *jointtech*, supporting the importance of technological characteristics for joint technological agreements. However, the correlation of the employee information with technological characteristics hints at organizational and financial drivers of alliance formation and the importance to control for such drivers.

[5]In other words, adding one more firm to a sample of N firms yields N more firm-pair observations. The number of new firm-pair observations is inflated compared to the number of independent observations containing the same amount of information.

Table 3.1: *Mean, standard deviations and correlations* [a]

		Mean	S.D.	1	2	3	4	5	6
Jointtech	(1)	0.02	0.13						
SumLnPC	(2)	8.77	2.94	0.09*					
AbsDiffLnPC	(3)	2.38	1.75	0.06*	0.14*				
Overlap	(4)	0.32	0.23	0.04*	0.57*	-0.37*			
Overlap^2	(5)	0.15	0.17	0.04*	0.51*	-0.35*	0.95*		
SumLnEmpl	(6)	13.11	3.41	0.07*	0.56*	0.23*	0.22*	0.23*	
AbsDiffLnEmpl	(7)	2.74	2.05	0.08*	0.16*	0.34*	-0.15*	-0.18*	0.29*

[a] N=20910 firm-pairs from crossing 205 firms; * signifies 0.1% rejection level of significance.

Ego-network structures. We present a graphical analysis of the results on ego-network statistics and position in the knowledge space. We argued above that firms near the center of the space should have differently structured ego-networks than those near the periphery. Because the model makes some very specific assumptions about the space and the distribution of firms within it, and because it is difficult to create a knowledge space empirically, we cannot do a direct test of the analytic results. However, the figures below suggest that they do conform to what we can observe.

Figures 3.2 and 3.3 provide a coherent picture of the case in which centrality in technological space leads to high centrality in the network and a higher number of triads.

Our data on knowledge allows us to compute for each firm not its position in knowledge space, but rather its distance from all other firms. There are several algorithms to take this information and project it onto a two-dimensional plane. In figure 3.2 we do this using the Fruchterman-Reingold algorithm.[6] Having positioned the firms in knowledge space, we superimpose their alliance network: lines between two points indicate the presence of an alliance between those two firms; the size of a point corresponds to the log-transformed number of alliances. It seems that firms more central in knowledge space also have higher degree centrality in the network. Technological distance of most alliances is rather short. Most alliances span at most half the technological space and there are no alliances, which span the entire space. Note that this strengthens our previous observation on alliance formation above that alliances are more frequent for technologically close firm-pairs. Furthermore, it suggests that the technological distance over which an alliance can be successful is small relative to technological space. This corresponds to a small benefit-distance range in the theoretical model, which implies that we should be interested in the second case $(a + (a + b) < 1)$

[6]This algorithm optimizes the positions against two criteria: covering the plane, and placing pairs of firms with low distance close to each other. The mapping is not unique, but we have presented here a representative mapping of a sample of 100 such mappings.

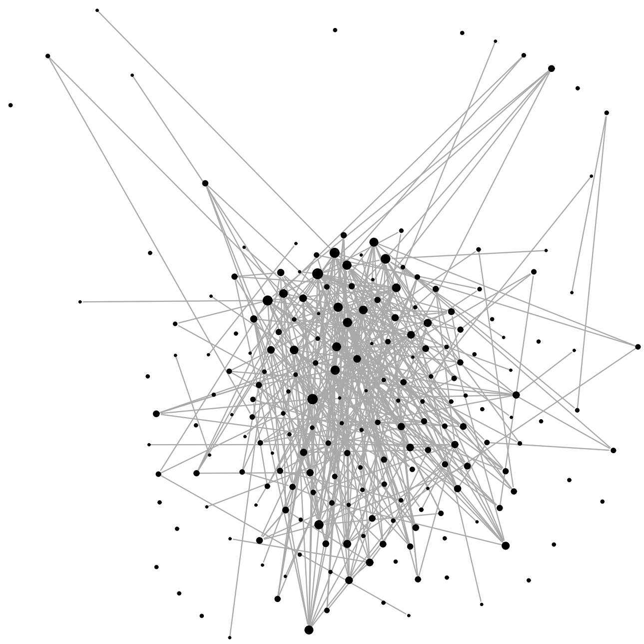

Figure 3.2: The network of joint technological agreements. Nodes are mapped into two dimensional knowledge space based on firm-pair overlap using the Fruchterman-Reingold algorithm. Size of the nodes equals log of degree.

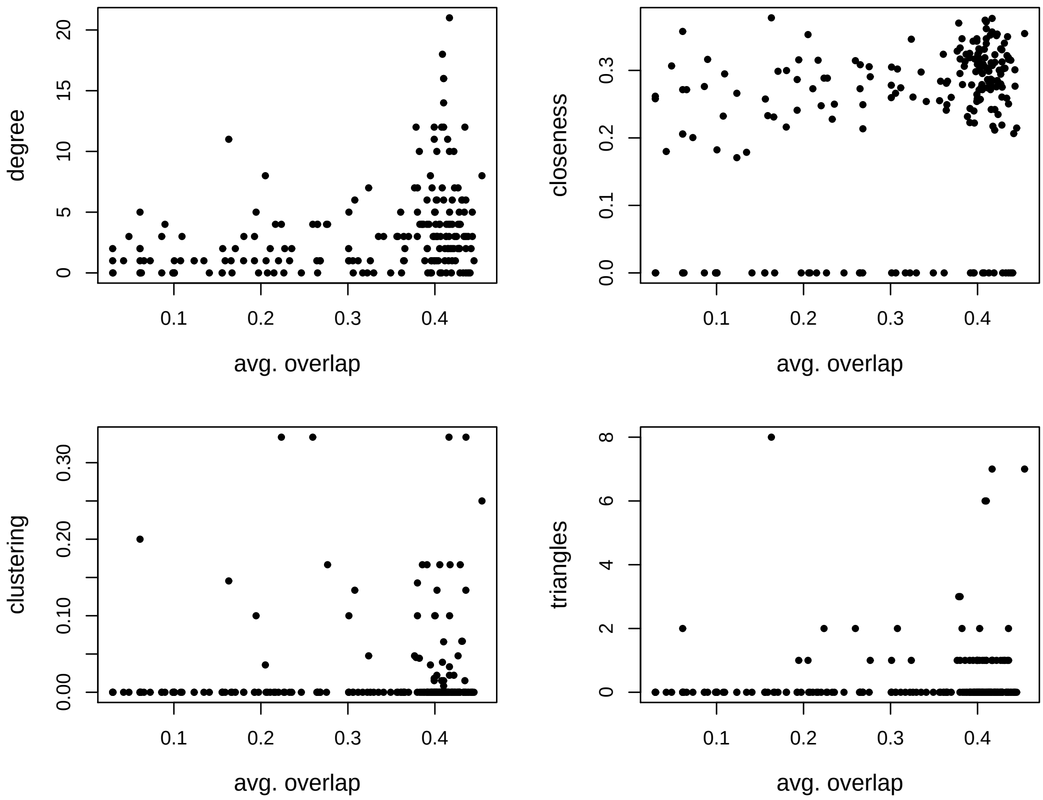

Figure 3.3: *Ego-network structure by average overlap. The higher the overlap to all other firms in the sample, the more central a firm is in technological space. Firms having a degree or closeness centrality of zero are singletons, not connected to the network.*

as derived in chapter 2, section 2.4.

This is confirmed in figure 3.3, where the average overlap of one firm to all other firms measures the firm's position in technological space. Firms with large average overlap are close to most other firms and, therefore, can be considered to be close to the center of the technological space. The top left panel in figure 3.3 plots degree centrality as a function of average overlap. It seems that the population is divided at an average overlap of 0.3. There are only two firms which are distant from the technological center (average overlap below 0.3) and yet have more than five alliances in the sample. Although there are firms which are close to the center in technological space (overlap above 0.3) and have few alliances, firms closer to the technological center in general have more alliances. The absence of any firm being at the boundary of technological space and having a high degree even suggests that being central in technological space is a prerequisite for having many research alliances.

The effect on closeness centrality, shown in the top right panel in figure 3.3, is less clear cut. Here, the Pearson's correlation between expected and observed firm network characteristics, with a coefficient of 0.34 and a significance level below 0.001%, gives a clear indication. Again, firms located near the center of the technological space tend to have a high closeness centrality. However, the clustering coefficient, given in the bottom left panel, deviates from theoretical prediction in that it is higher for firms being close to the technological center. In the model in case 2 ($1 < 2a + b$), firms at the center have relatively a high number of triangles but due to having high degree, their clustering becomes low. In our sample firms at the center do have a high number of triangles as well as a high degree (see upper left and lower right panels). However, their degree is not high enough to cause a low clustering coefficient.

Global network structures. The global network structure is characterized by the distributions of network measures. Locating the distributions of the sample network in parameter space of the theoretical model is not attempted here because the model assumptions naturally lead to a discrepancy between empirical and theoretical distributions. The deterministic decision making in the model leads an agent to connect to all agents within its profitable range, which is a fraction of the population. In reality, firms are going to connect only to individual agents within their profitable range because accessing many agents with similar knowledge is not beneficial. In addition, the model assumes that knowledge space is continuously populated whereas population in real world is probably both less dense and less uniform.[7]

Both assumptions lead to theoretical networks which are denser than the sampled network. Thus, the average degree of theoretical networks generally is higher than of the sampled network. Comparing the means of the other distributions, we find that theoretical distributions of closeness, clustering and triangles also have a higher mean in large regions of parameter space (see first column of table 3.2 and figures 2.3, 2.5, 2.7 in chapter 2, section 2.4.). Furthermore, the magnitudes of the coefficients of variation and skewness of theoretical distributions are generally lower than of the sampled distributions. Therefore, attempting to pin down the parameters a and b for the observed network measure distributions is not promising. A second sample network is needed to provide a reference point. Then, comparing the network measure distributions of two networks might allow to conclude on the relative shape of the benefit-distance effects working in each sample.

A further observation on the theoretical model is that the relation of network measure distributions is the same over the whole parameter space. For example if average degree centrality is high, average closeness centrality tends to be high. The close relation of network measures is caused by definition of the network measures (for example

[7] See also the model discussion in chapter 2, section 2.4.

Table 3.2: Moments of network measure distributions

	Mean	S.D./Mean	Skewness
Degree	3.31	1.09	1.98
Closeness	0.23	0.02	-1.08
Clustering	0.02	0.003	3.35
Triangles	0.41	1.33	4.47

degree enters the calculation of closeness centrality) but is also due to the model assumptions. Note that a close relation is also observed for the sampled distributions. All sample distributions have low means and high coefficients of variation and skewness. In this respect observed distributions are consistent with the theoretical model.

Statistics summary In sum, our statistical evidence is internally consistent with the model results. Firstly, alliance formation potentially is driven by technological distance. Firm-pairs which form alliances have smaller technological distances than firm-pairs which do not form alliances. Secondly, the observed relationship of the firms' position in technological space and their network characteristics is implied by the second case of the model. Thirdly, observed network measure distributions are similarly related to each other as are theoretical distributions; although on a lower level. The empirical relevance of the model is further confirmed by inductive statistics, which follow now.

3.4.4 Testing Strategy

To test the first hypothesis, the effect of technological distance on joint technological agreements is estimated. The estimates assign to each firm-pair a probability of forming an alliance and, when aggregated, yield expectations on the network. The expected network implies both expected firm network positions and expected network measure distributions. The relevance of the local effect on the network is revealed by comparing the expected with the observed firm network positions (hypothesis two) as well as with the network measure distributions (hypothesis three). The next paragraphs discuss these steps in more detail.

Alliance formation A logit function is an appropriate model for the decision of two firms to form an alliance. However, when estimating link formation in a network, the non-independence of observations is an issue (van Duijn and Vermunt, 2006). An important source of dependence is the repeated observation of one firm over several firm-pairs. This is likely to cause correlated errors over firm-pair observations, because some firms are more susceptible to form alliances than others for unknown reasons. In this case, maintaining the independence assumption under-estimates standard errors and potentially gives biased coefficient estimates.

This problem is similar to that of repeated observations of one firm over time in a panel. In the panel setting, the problem is usually handled by introducing unobserved firm specific effects (Cameron and Trivedi, 2005). Under the assumption that firm specific effects are uncorrelated with other independent variables, one estimates a random effects model. When correlated, the random effects model yields biased coefficient estimates and the less efficient fixed effects model is appropriate. Which model to choose is based on a Hausman test, which tells whether the coefficients can be assumed to be equal given their variances.

We apply the standard solution for panel data to the estimation of link formation in a network. Different from panel data though, we are handling dyads. Therefore, the conditional probability that firm-pair ij forms an alliance is conditional not on one but on two unobserved firm specific effects, a_i and a_j, and the Logit model becomes

$$Pr[jointtech_{ij} = 1 | x_{ij}, a_i, a_j] = \frac{\exp(x'_{ij}\beta + a_i + a_j)}{1 + \exp(x'_{ij}\beta + a_i + a_j)},$$

where x_{ij} is a vector of dyadic-covariates and β the corresponding coefficients. As is common for panel data models, we distinguish random and fixed effects. A random effects model to estimate link formation in a network has been proposed by (Hoff, 2003). We estimate it by maximum simulated likelihood under the assumption that firm specific effects are independently normally distributed. The fixed effects model is estimated with maximum likelihood by introducing a dummy variable for each firm (an approach already taken by Stuart, 1998). This does not cause the incidental parameter issue because the number of firm-pairs (observations) increases much faster then the number of firms (variables). However, firms which have no links with other firms in the sample need to be excluded, because their fixed effect is minus infinity (not defined). This is not the case for the random effects model, where the inclusion of these firms rather increases the variance of the random effects distribution. Because the Hausman test showed that the coefficient estimates of the random effects model are similar to those of the fixed effects model, we present only the results of the more efficient random effects model; estimated on the complete sample. Econometric details and results for fixed and random effects estimation are given in appendix B.1.

Introduction of firm specific-effects does not necessarily make observations independent. Errors might still be systematically correlated, for example when firms favor alliances with firms that are already close in the network. One strategy is to incorporate sufficient statistics for different kind of dependencies, as in the framework of Markov Graphs (van Duijn and Vermunt, 2006). The problem is that estimation might not be possible for some (larger) networks (Hunter et al., 2007), which happened in our case when introducing statistics of a dyadic dependence model. Because firm specific-effects probably control for the most important source of bias and variance deflation, we leave the problem of more complicated network dependencies to future research.

Ego-networks The estimates obtained from the Logit model are used to form expectations on the firm network positions. In principle expectations can be analytically derived. For example the expected degree centrality of a firm is simply the sum of the probabilities of link formation over all firm dyads that include the focal firm. Analytical derivation of the expectations of the other network measures is more complicated but easily obtained by simulation. The estimates of alliance formation can be used to create a probabilistic adjacency matrix: the probability that each potential alliance exists. One instance of a network is simulated by random realization of all links given this probabilistic adjacency matrix. From each simulated network the position of each firm in terms of degree, clustering, closeness and number of triangles is calculated. Then, the average over many such simulations yields the expected firm position. The presented expectations are based on 1000 simulations, sufficient that different runs give the same results. Significant correlation of the expected network positions with the observed ones would corroborate hypothesis two.

Global networks Hypothesis three is similarly tested by comparing the expected with the observed network measure distributions. From each simulated network the network measure distributions are obtained. Their average gives the expected network measure distributions. Visual comparison of the distributions is valuable to judge the validity of hypothesis three (Hunter et al., 2008). In addition, we use the Kullback Leibler Information Criterion (KLIC) to measure the distance from the expected to the observed network measure distributions.[8]

3.5 Results

3.5.1 Hypothesis Testing

Hypothesis 1, Alliance Formation

Table 3.3 reports the results of the regression analysis on the effect of technological distance on joint technological agreements. The estimations support the first hypothesis. There is a curvilinear relationship between our structural measure of technological distance, *overlap*, and joint technological agreements, *jointtech*. Furthermore, we find a

[8]The KLIC for discrete distributions equals $KLIC(p,\pi) = \sum p(y)\ln(p(y)/\pi(y))$ and measures how close the distribution $p(y)$ is to a reference distribution $\pi(y)$. $KLIC(p,\pi)$ is strictly convex, $KLIC(p,\pi) > 0$ always and $KLIC(p,\pi) = 0 \iff p = \pi$. We calculate the KLIC for discrete distributions because our reference distribution, the observed network measure distribution, is discrete. This makes necessary to discretize the expected network measure distributions. The discretization is presented together with the results.

preference to combine with unequal partners regarding the size of the patent portfolio as well as firm size.

In table 3.3, model 1 is the baseline equation, containing only the firm size control variables. The sum and absolute difference of log-employees (*sumLnEmpl* and *absDiffLnEmpl*) are positive, showing that big and small firms are likely to ally. This is in accord with previous findings on the interdependencies of small and big firms in the pharmaceutical industry (Powell et al., 2005). Model 2 adds the sum and absolute difference of patent portfolio sizes (*sumLnPC* and *absDiffLnPC*). Their significance and a decreasing Akaike Information Criterion (AIC) assigns high relevance to both variables. The decrease of the coefficients on the size control variables supports the idea that the interdependencies between big and small firms are partly technological. Model 3 adds the second dimension of technological distance namely *overlap*. It supports hypothesis one of a curvilinear relationship, with *overlap* being positive and $overlap^2$ negative.

The estimated point of optimal technological distance is the value of overlap where the probability of forming an alliance is maximal. For the logit function, derivation of the linear regressor with respect to *overlap* yields a point of optimal technological overlap of 0.77. Thus, the inverse-U-shaped benefit-distance effect has an internal maximum. More specifically, the probability of alliance formation increases with increasing technological distance from one overlap (no distance) up to an overlap of 0.77 and then decreases again until zero overlap (the maximum distance) is reached.

Table 3.3: *Random effects logit models of alliance formation (jointtech)* [a]

	Model 1		Model 2		Model 3	
Intercept	-7.23***	(0.347)	-7.78***	(0.364)	-8.37***	(0.422)
Overlap	–		–		4.12***	(0.987)
Overlap^2	–		–		-2.69**	(1.032)
SumLnPC	–		0.21***	(0.026)	0.11***	(0.032)
AbsDiffLnPC	–		0.09**	(0.033)	0.21***	(0.042)
AbsDiffLnEmpl	0.23***	(0.026)	0.2***	(0.029)	0.21***	(0.030)
SumLnEmpl	0.16***	(0.019)	0.04*	(0.023)	0.05*	(0.024)
σ^2 [b]	0.35	(0.095)	0.35	(0.097)	0.38	(0.099)
AIC	3287.05		3208.87		3186.22	

[a] N=20910 firm-pair observations from crossing 205 firms; standard errors in brackets; *,**,*** signify 5%, 1% and 0.1% rejection levels of significance.
[b] The estimate of random effects variance follows a log-normal distribution and are therefore strictly positive.

In order to test hypothesis 1, three models estimated local effects of network formation: the first model the heterophily of big and small firms, the second model adds the heterophily of firms with big and small patent stocks and the third model adds the distance benefit relationship of technological distance. All effects are significant — separately and jointly.

Hypothesis 2, Ego-Network Structures

Hypothesis 2 proposes that network characteristics of a firm depend on its position in the knowledge space and that the relationship is determined by the benefit-range (parameters a and b in the model). Based on a numerical simulation of networks using the model estimates obtained above, we derived the expected network position of each firm. Correlation of expected with observed network positions shows how well the respective model of dyad formation explains the higher-level phenomenon of a firm's network position.

Table 3.4 partially supports the hypothesis. The first model, only taking into account the size of the firms, is capable of predicting degree centrality and number of triangles. Adding the size of the patent portfolios in model 2 improves the predictive power for degree, triangles and especially closeness. Predictions of all three measures improve significantly from model 1 to model 2, i.e. the null hypothesis that correlation coefficients of model 1 and model 2 are equal is rejected below or equal to the 5% significance level (see rows '$P_{m=m-1}$', column 'model 2').[9] Correlations between observed and estimated values increase when the distance benefit relationship (in terms of overlap and its square) are included. However, model 3 improves model 2 predictions only for degree significantly at a 2.4% rejection level. Once the information on the size of the patent portfolios is taken into account, adding the structural information of technological position does not significantly improve predictions of the firms' closeness centrality or triangles (see rows '$P_{m=m-1}$', column 'model 3'). Clustering is not well explained by any of the models. Probably due to the low number of triangles in the network and the normalization by degree it is very difficult to predict.

In sum, we find that including the firm position in technological space, in model 2 the size dimension and in model 3 the structural dimension, helps to explain the firm position in network space. Introduction of the size dimension improves predictions considerably. Further improvements by adding the structural dimension are relatively small.

[9] Tests for the null hypothesis that correlation coefficients for two models are equal are based on Williamson's test statistic for dependent correlation coefficients as described in Steiger (1980, p.246); all tests are one-sided.

Table 3.4: *Pearson's correlation of observed and expected firm ego-network statistics* [a]

		Model 1	Model 2	Model 3
Degree	r_m [b]	0.49***	0.61***	0.64***
	$P_{m=m-1}$ [c]	–	0.001	0.024
Closeness	r_m	0.13	0.3***	0.33***
	$P_{m=m-1}$	–	0.003	0.223
Clustering	r_m	-0.07	-0.03	0.00
	$P_{m=m-1}$	–	0.181	0.437
Triangles	r_m	0.19**	0.31***	0.32***
	$P_{m=m-1}$	–	0.050	0.130

[a] Expectations are based on estimates of the random firm effects model in a monte carlo approach with 1000 draws.

[b] r_m denotes the correlation coefficient; *,**,*** signify 5%, 1% and 0.1% significance level of zero correlation.

[c] $P[r_m = r_{m-1}]$ is rejection level of the null hypothesis that correlation coefficients of models m and $m-1$ are equal.

Hypothesis 3, Global Network Structures

Hypothesis 3 proposes that network measure distributions depend on the firms' locations in knowledge space. This hypothesis is supported but the effect is weak. The firms' technological characteristics, i.e. sizes of patent stocks and overlap in IPC classes, improve the explanation of the observed network measure distributions only slightly after the size of firms is taken into account.

Figure 3.4 compares observed with expected network measure distributions. The performance of the three models can be judged by how they improve the random model.[10] The random model of alliance formation contains no firm information but only an intercept and, therefore, the probability that an alliance forms is the same for all firm-pairs. Interestingly, the random model generates a centralized network with some clustering/triangles. However, centralization and clustering/triangles are different to the observed network and introduction of firm-level information improves the expected distributions.

For all four network measure distributions we find a big improvement from the random model to model 1, where firm size is introduced. Introduction of the firm position in knowledge space, with model 2 and model 3, yields minor improvements relative to model 1.

The degree distribution is met best. The reason is that the regression estimates dyad formation and this is highly related to degree, which is simply the sum over all dyads formed by a firm. The other measures depend on more complex network structures which have not been included in the estimation of coefficients. Closeness takes into account the whole network, triangles the links between three firms and clustering the ratio of triangles to density.

One important result is that network measures which capture the structure of the network are better predicted simply by introduction of exogenous factors in the model of pairwise alliance formation. If a model is capable of reproducing the observed network structure without including references to it, in form of network statistics either as regressors or as optimization objectives, then the network structure might not be endogenously but exogenously determined.

3.5.2 Sensitivity Analysis

The results discussed above are based on the random effects logit, which assumes that firm specific effects are not correlated with other covariates. Besides the random effects logit, we estimated a fixed effects logit and compared the coefficients using a Hausman test. The Hausman test shows that both models yield similar coefficient estimates, which justifies focusing on the random effects model. For discussion and results of the random versus fixed effects estimations see Appendix B.1.

[10] The random model is also known as Erdös-Rényi model.

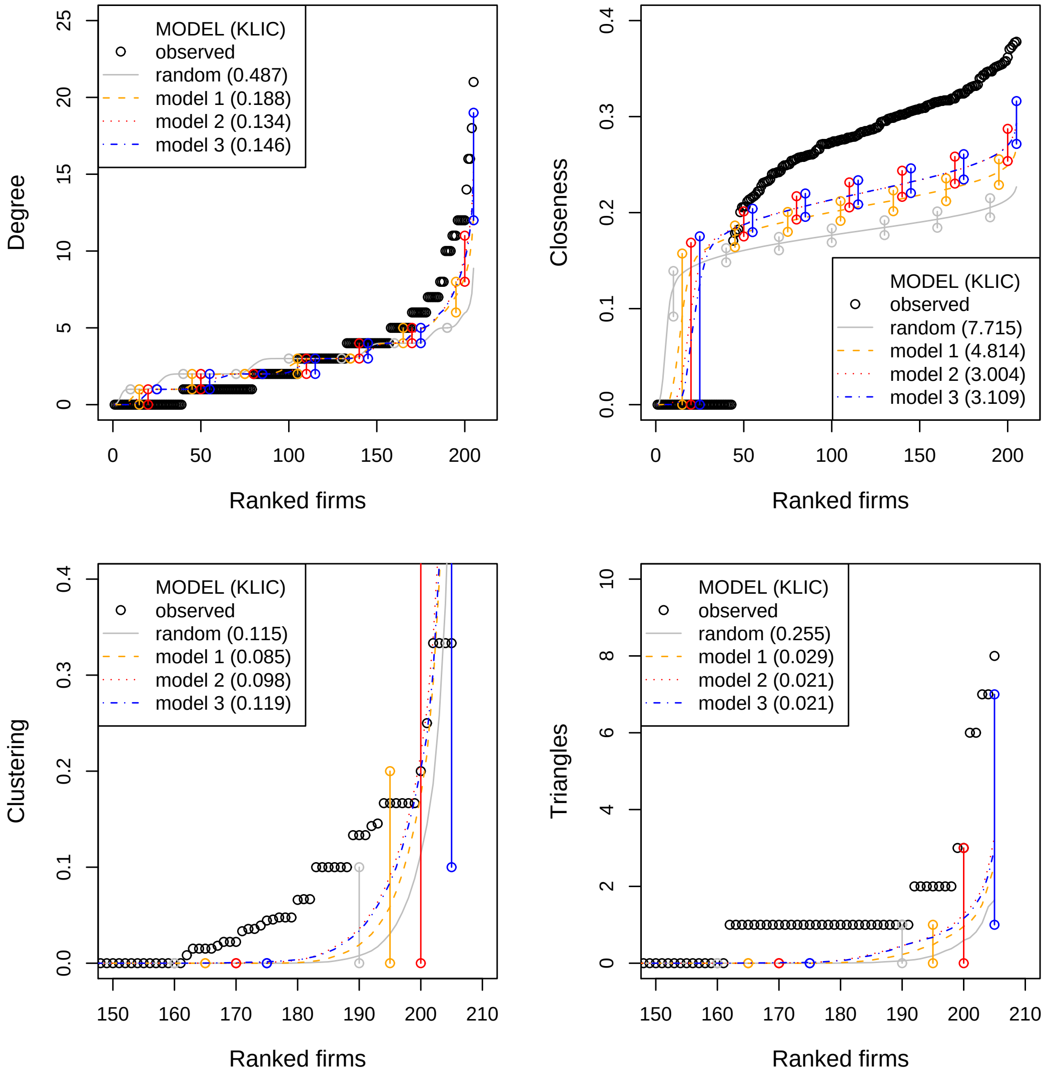

Figure 3.4: *Observed and expected network measure distributions. Black circles are observations, lines give the average over 1000 simulations, circles connected by vertical lines indicate 90%-confidence intervals. KLIC compares probability masses according to the following cutpoints: degree (1, 2, 3, 5), closeness (0, 0.258, 0.287, 0.317), clustering (0, 0.015, 0.041, 0.1, 0.167), triangles (1, 2).*

A further issue might be the inclusion of firms with few patents. Patents signal the technological position of firms. When a firm applies for only a few patents during the period of observation, the signal might not give the full range of technological fields a firm in fact covers. Then, the firm might be wrongly taken as being at the boundary of technological space. The sensitivity of our results with respect to this issue is tested on firms having more than five patents and thus signals more reliably their position. This restriction makes little change to the coefficient estimates, whereas the level of significance of $overlap^2$ increases to 5%. This is due to a higher standard error along with the reduced number of observations. Therefore, regression on the restricted sample supports hypothesis 1. Also, tests of hypothesis 2 and hypothesis 3 give results that are equal in magnitude and significance to the results already discussed above.

Finally, other distance measures than overlap have been applied. We repeated the analysis for the uncentered correlation of firms technology vector, introduced by Jaffe (1986, 1989), and the correlated revealed technological advantage (cRTA), introduced by Soete (1987); Patel and Pavitt (1987). These measures have been developed for different reasons. As its predecessor, revealed comparative advantage, revealed technological advantage (RTA) has been applied to compare the relative specialization of countries. Jaffe (1986) aggregated all IPC classes into 49 technology fields to calculate the uncentered correlation for firms of various sectors.

Whereas cRTA is highly significant when regressing joint technological agreements, uncentered correlation is not. The estimation of pairwise alliance formation using cRTA finds a strong preference for technological proximity which is significant but does not confirm the hypothesized inverse-U-shape of the benefit-distance relationship. The support for hypotheses two and three using cRTA is similar in strength to those presented in the previous section. However, predictions of the firm's ego-network structure are different for the overlap and cRTA measure. Whereas the overlap measure improves especially predictions of the firm's degree centrality, cRTA improves predictions of the firm's number of triangles. One reason for this finding might be that the two measures capture different aspects of the structure provided by the technological space. Therefore, considering results on both distance measures further supports hypothesis 2 that the position of firm's in network space depends on their position in technological space. However, the uncentered correlation measure does not improve predictions; neither of ego-network structures nor of global network structures. Thus, estimation with alternative distance measures partly supports the existence of a local technological distance effect on the network. Also, the exact shape of the local effect depends on the distance measure.[11]

[11] Appendix B.2 provides the results on alternative measures of technological distance as well as the sample restriction on firms having a minimum number of patents.

3.6 Discussion and Conclusion

In this chapter we investigate empirically how the technological position of firms affects network formation. In the theoretical model of the previous chapter, we assumed an inverse-U-shaped relationship between distance and benefit for two firms forming an alliance (Cohen and Levinthal, 1990; Nooteboom et al., 2007). This assumption is empirically confirmed for the overlap measure, which strengthens prior empirical findings (Mowery et al., 1998).

However, the sensitivity analysis shows that different measures of technological distance yield different results. Using correlated revealed technological advantage, alliance formation is most likely for technologically close firms, as observed by Stuart (1998). Uncentered correlation is not significant. From a technical point of view, the different results arise because the information provided by the patent portfolio is differently used and transformed. An interpretation, however, is that different measures of technological distance capture different aspects of the technological relation of two firms. It is likely that firms consider a great variety of technological aspects which influence their decision to form an alliance in different ways. The way we construct the technological relatedness of two firms, i.e. the choice of the distance measure, is likely to determine which aspects are emphasized and which are neglected in our measurement. Therefore, one would be even surprised if different measures of technological distance would yield the same results.

The theoretical model shows how certain benefit-distance specifications affect the network structure and firm positions. The main insight of the theoretical analysis is that if alliance formation is beneficial for technologically close (distant) firm-pairs, then firms which are in the center (at the boundary) of the knowledge space are going to be central in the research network.

The empirical analysis finds this effect in the pharmaceutical industry. We provide statistics showing that firms in the center of technological space are also in the center of the network. In the econometric analysis, however, the effect of the benefit-distance relationship on the firms' position in the research network becomes small once the size information of the firms' patent portfolio is taken into account. Thus, a description of the technological position of the firm best includes a size dimension, here the size of the patent portfolio, and a structural dimension, here the benefit-distance relationship.

Our finding on the importance of the size dimension of the firm's technological position supports previous findings of Ahuja (2000). He proxies the firm's technological capital by patent portfolio size and also finds it highly relevant for the firm's number of alliances; one aspect of the firm's ego-network.

The fact that we find the benefit-distance effect to be relevant for the position of the firm in the network yields management implications. In the short run, management cannot freely envisage profitable network positions but is bounded by the firms technological endowment. This needs to be considered in the technology strategy of the firm.

Firms that focus on distant technological niches to reduce competitive pressure might find themselves isolated in the research network as well. Considering opportunities for cooperation besides unique technological qualification is crucial, because research alliances are important sources of financing and internal technological development.

The empirical analysis on the network level assigns a weak role to the benefit-distance relationship. It does not improve significantly the predictions based on firm size effects. Whereas any of our models predicts the degree distributions very well, predictions of the other network measures might be improved. The next chapter studies whether social network factors in a model of alliance formation are more informative.

APPENDIX B

Econometric Analysis

B.1 Random and Fixed Effects

B.1.1 Models and Estimation

For the logit model with firm specific effects the conditional probability of alliance formation is:

$$p_{ij} \ = \ Pr[y_{ij} = 1 | x_{ij}, a_i, a_j] = \frac{\exp(x'_{ij}\beta + \ a_i + \ a_j)}{1 + \exp(x'_{ij}\beta + \ a_i + \ a_j)} \ ,$$

where p_{ij} is the probability that firm i and j form an alliance (i.e. $y_{ij} = 1$), x_{ij} is a vector of dyadic-covariates, and a_i and a_j are firm specific effects. The model assumes that firm specific effects are the only source of dependence and hence, given a_i and a_j, the dyadic observations are assumed to be independent.

Estimation of the fixed effects model is done with introduction of firm dummies (see also Stuart, 1998). A necessary assumption for asymptotic theory to hold is that the number of parameters is fixed whereas the number of observations goes to infinity. This assumption is approximately given because the number of firm specific effects increases with n (number of firms) whereas the number of observations increases with $n(n-1)/2$ (number of firm-pairs). Therefore, estimation of the fixed firm effects model is feasible with Maximum Likelihood.

However, direct estimation of firm dummies is inefficient. To estimate the more efficient random effects model, the firm specific effects are integrated out. We do this with a direct monte carlo simulator under the assumption that the a_i are independent and identical distributed (i.i.d.) according to a normal distribution $N(0, \sigma^2)$. Each draw yields a random realization of all firm specific effects and allows to calculate the conditional probability for each observation. The average of S draws yields the simulated probability, $\hat{f}(\cdot)$, now conditional on known (simulated) firm specific effects and the variance of the distribution, which as well needs to be optimized:

$$\hat{f}(y_{ij}|x_{ij}, a_{is}, a_{js}, \sigma) = \frac{1}{S}\sum \frac{\exp(x'_{ij}\beta + \sigma a_{is} + \sigma a_{js})}{1 + \exp(x'_{ij}\beta + \sigma a_{is} + \sigma a_{js})}$$

where the a_{is} are i.i.d. draws from $N(0,1)$ and transformed to firm specific effects by multiplication with the parameter σ. The simulated densities enter the maximum simulated likelihood estimator, which maximizes:

$$lnL(\beta) = \sum \ln \hat{f}[y_{ij}|x_{ij}, a_{is}, a_{js}, \sigma]$$

over all firm-pairs. As long as $S, N \rightarrow \infty$ and $\sqrt{N}/S \rightarrow 0$, the single simulations (one draw) are unbiased and the usual assumptions for likelihood estimation apply. Then, the estimator has a limit normal distribution

$$\sqrt{N}(\hat{\theta}_{MSL} - \theta_0) \xrightarrow{d} N[0, A^{-1}(\theta_0)],$$

where

$$A(\theta_0) = -plim\left[N^{-1}\sum \frac{\delta^2 \ln f(y_{ij}|x_{ij}, \theta)}{\delta\theta\delta\theta}\right]$$

(see Cameron and Trivedi, 2005, p.393ff). The variance matrix is needed to derive confidence intervals and can be estimated in various ways. We choose the simplest estimator which is the BHHH estimate for the information matrix (see Cameron and Trivedi, 2005, p.393ff).

The simulated likelihood is estimated with the iterative Broyden-Fletcher-Goldfarb-Shanno (BFGS) method. Here, as in other optimization procedures (e.g. Newton-Raphson, BHHH) the direction of the steps towards the optimum is given by the gradient in the current step and the size of the step is determined by the slope of the likelihood-function. The difference is that whereas other approaches use information for the slope only given by the current position (for Newton-Raphson the Hessian matrix, for BHHH the information matrix), BFGS determines the slope of the likelihood function by differences of the gradient caused by non-marginal position changes. This gives speed advantages in non-simple environments (Train, 2003, p.201).

For optimization we use the optim function in the R-stats-package to which we provide the simulated likelihood function:

$$lnL(\beta) = \frac{2}{N(N-1)}\sum_{i=1}^{N}\sum_{j=i+1}^{N(N-1)/2} \ln \frac{1}{S}\sum_{s=1}^{S}\left(\frac{\exp(\cdot)}{1+\exp(\cdot)}\right)^{y_{ij}}\left(\frac{1}{1+\exp(\cdot)}\right)^{1-y_{ij}},$$

where $\exp(\cdot) = \exp(x'_{ij}\beta + \sigma a_i + \sigma a_j)$. To ensure a positive variance σ, we optimize $log(\sigma)$ which results in a log-normal distribution for its standard error. Because there is no principal difference between β and σ in the following, we combine them to θ with indicators for firm specific effects also incorporated in x_{ij}. In order to increase estimation speed, we derive the gradient of the MSL estimator.

$$\frac{\delta lnL(\theta)}{\delta\theta} = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N(N-1)/2} \left(\frac{\delta \frac{1}{S} \sum_{s=1}^{S} \left(\frac{\exp(\cdot)}{1+\exp(\cdot)}\right)^{y_{ij}} \left(\frac{1}{1+\exp(\cdot)}\right)^{1-y_{ij}} / \delta\beta}{\frac{1}{S} \sum_{s=1}^{S} \left(\frac{\exp(\cdot)}{1+\exp(\cdot)}\right)^{y_{ij}} \left(\frac{1}{1+\exp(\cdot)}\right)^{1-y_{ij}}} \right)$$

because $\frac{\delta \ln f_{ij}}{\delta\theta} = \frac{\delta f_{ij}/\delta\theta}{f_{ij}}$ and after some calculation

$$\frac{\delta lnL(\theta)}{\delta\theta} = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N(N-1)/2} \left(\frac{\frac{1}{S} \sum_{s=1}^{S} \left(\left(y_{ij} x_{ij} \frac{\exp(\cdot)^{y_{ij}}}{(1+\exp(\cdot))^2} \right) - \left((1-y_{ij}) x_{ij} \frac{\exp(\cdot)^{1+y_{ij}}}{(1+\exp(\cdot))^2} \right) \right)}{\frac{1}{S} \sum_{s=1}^{S} \left(\frac{\exp(\cdot)}{1+\exp(\cdot)}\right)^{y_{ij}} \left(\frac{1}{1+\exp(\cdot)}\right)^{1-y_{ij}}} \right)$$

Comparison of fixed and random effects models is based on the simplified version of the Hausman test. Under the assumption that the random effects estimate is fully efficient, the covariances among the coefficients of the two models equal the variance of the efficient model coefficients (Cameron and Trivedi, 2005, p.272). This allows for separate estimation of both models, which simplifies the Hausman test.

B.1.2 Results

In the fixed effects model the firm dummy controls for the overall alliance activity of the firm. If for a firm no alliance is observed, the dummy coefficient takes on minus infinity and hence is not defined. Therefore, a comparison of fixed and random effects can only be done on the restricted set of 166 firms, which have alliance partners in the network.

Table B.1 gives the results of the random and fixed effects models as well as the Hausman test, which compares their coefficients. Except for *absDiffLnPC*, for no coefficient the null hypothesis of random and fixed effects estimation being equal can be rejected. This justifies to base the analysis in the main text on the random effects estimates.

The random effects model coefficients *overlap* and *overlap*^{2} are still significant when estimated on the restricted firm sample. However, compared to the estimation on the complete sample magnitude decreases (see table 3.3 in the main text). Figure 3.2 reveals the reason: many firms with no alliance partners are at the boundary of the knowledge space; which supports hypothesis one. In the fixed effects model *overlap* and *overlap*^{2} are not significant. Although the Hausman test confirms that coefficients are similar to the random effects estimation, increasing standard errors prevent significance. This effect can be largely attributed to the efficiency loss due to

Table B.1: Hausman's test (model 3) [a]

	Random Effects		Fixed Effects [b]		H-Value	$Pr(>\|H\|)$ [c]
Intercept	-7.24***	(0.429)	–		–	–
Overlap	3.5***	(1.002)	2.28	(1.823)	0.64	0.42
Overlap^2	-1.88*	(1.047)	-1.79	(1.729)	0.00	0.95
SumLnPC	0.06*	(0.032)	-0.01	(0.910)	0.00	0.94
AbsDiffLnPC	0.25***	(0.042)	0.14**	(0.061)	5.91	0.02
SumLnEmpl	0.03	(0.024)	-0.47	(1.015)	0.24	0.62
AbsDiffLnEmpl	0.21***	(0.031)	0.18***	(0.037)	1.92	0.17
σ^2	0.49	(0.108)	–		–	–
AIC	2964.66		3008.28		–	–

[a] N=13695 firm-pair observations from crossing 166 firms. Standard errors in brackets; *,**,*** signify 5%, 1% and 0.1% rejection levels of significance.

[b] Firm dummy estimates not displayed.

[c] $Pr(>|H|)$ is significance level of rejection of equality of coefficients from chi-square distributed H-value with 1 d.o.f.

firm dummy estimation. Therefore the fixed effects estimation does not necessarily refuse hypothesis one. The heterophily of big and small firms in terms of patent counts and employees is confirmed in both models. Although, the coefficient capturing the difference in the number of patents changes significantly, it remains positive and significant even in the fixed effects model. In total, the comparison of random and fixed models justifies the focus on the random effects model and further supports hypothesis one.

B.2 Sensitivity Analysis

The sensitivity analysis employs a restricted estimation set as well as alternative measures of technological proximity. As in the main analysis, we estimate i) the benefit-distance effect on alliance formation of firm-pairs and then use these estimates to predict ii) the ego-network of the firm and iii) global network structures. The estimation results on the restricted estimation set, which includes only firms with more than five patents, parallels results on the complete estimation set. The technological-distance effect on pairwise alliance formation is significant for one alternative measure of technological proximity (cRTA) but not for the other (uncCorr). Predictions of the firm's ego-network based on the significant distance measure cRTA improve predictions based only on the size of the firm and the size of its patent portfolio (model 2).

Results on global network structures are similar to the findings in the main analysis.

B.2.1 Restricted Estimation Set

The restricted estimation set includes only firms having more than 5 patents with priority date between the years 1995 and 2000. We repeat the analysis using the restricted estimation set because firms with few patents might not reliably signal their technological specialization.

Alliance formation We find that estimation of the benefit-distance effect is robust to the sample restriction. The inverse-U-shaped benefit distance effect remains significant (see overlap and overlap^2 in model 3, table B.2). Compared to the estimation results on the full sample, presented in table 3.3 in the results section 3.5, coefficients change only little with respect to standard errors. The increase of the significance level of the square of overlap is mainly due to increasing standard error along with the reduction of observations.

Table B.2: Random effects logit models of alliance formation (jointtech) - restricted sample [a]

	Model 1		Model 2		Model 3	
Intercept	-7.01***	(0.375)	-7.62***	(0.396)	-8.15***	(0.481)
Overlap	–		–		3.63***	(1.175)
Overlap^2	–		–		-2.24*	(1.219)
SumLnPC	–		0.18***	(0.029)	0.09**	(0.035)
AbsDiffLnPC	–		0.11**	(0.040)	0.21***	(0.047)
AbsDiffLnEmpl	0.23***	(0.027)	0.19***	(0.030)	0.2***	(0.032)
SumLnEmpl	0.15***	(0.020)	0.06*	(0.024)	0.06**	(0.025)
σ^2 [b]	0.41	(0.111)	0.35	(0.113)	0.33	(0.113)
AIC	2922.35		2874.24		2858.02	

[a] N=16653 firm-pair observations from crossing 183 firms; standard errors in brackets; *,**,*** signify 5%, 1% and 0.1% rejection levels of significance.
[b] The estimate of random effects variance follows a log-normal distribution and are therefore strictly positive.

Ego-network structures Predictions of ego-network structures in the restricted sample are comparable to those on the unrestricted sample. In comparison to model 1 (includes firm size only), model 2 improves significantly predictions of all aspects of the firm's ego-network except clustering by adding patent portfolio size. Model 3 further adds the benefit-distance relationship and thereby improves all predictions; improvement with respect to model 2 is significant for degree centrality at a 3.5% significance level (see degree, row $P_{m=m-1}$, column 'model 3' in table B.3).[1]

Table B.3: *Pearson's correlation of observed and expected firm ego-network statistics - restricted sample* [a]

		Model 1	Model 2	Model 3
Degree	r_m [b]	0.49***	0.59***	0.61***
	$P_{m=m-1}$ [c]	–	0.004	0.035
Closeness	r_m	0.17*	0.23**	0.27***
	$P_{m=m-1}$	–	0.076	0.161
Clustering	r_m	0.1	0.15*	0.19**
	$P_{m=m-1}$	–	0.174	0.105
Triangles	r_m	0.18*	0.28***	0.30***
	$P_{m=m-1}$	–	0.018	0.165

[a] Expectations are based on estimates of the random firm effects model in a monte carlo approach with 1000 draws.
[b] r_m denotes the correlation coefficient; *,**,*** signify 5%, 1% and 0.1% significance level of zero correlation.
[c] $P[r_m = r_{m-1}]$ is rejection level of the null hypothesis that correlation coefficients of models m and $m-1$ are equal.

Global network structures Results on the global network structure parallel the findings presented in the main text. Compared to the random model with intercept only, using the firm size information in model 1 improves expected distributions of network measures. In particular, expected distributions of degree and closeness approach observed distribution. Taking furthermore into account the technological position of the firm, i.e. the size of the patent portfolio and the benefit-distance relationship, yields minor improvements in prediction.

B.2.2 Alternative Measures of Technological Proximity

Alternative specifications We compare results on the three measures of technological proximity 'correlated revealed technological advantage' (cRTA), 'uncentered correla-

[1]Tests for the null hypothesis that correlation coefficients for two models are equal are based on Williamson's test statistic for dependent correlation coefficients as described in Steiger (1980, p.246); all tests are one-sided.

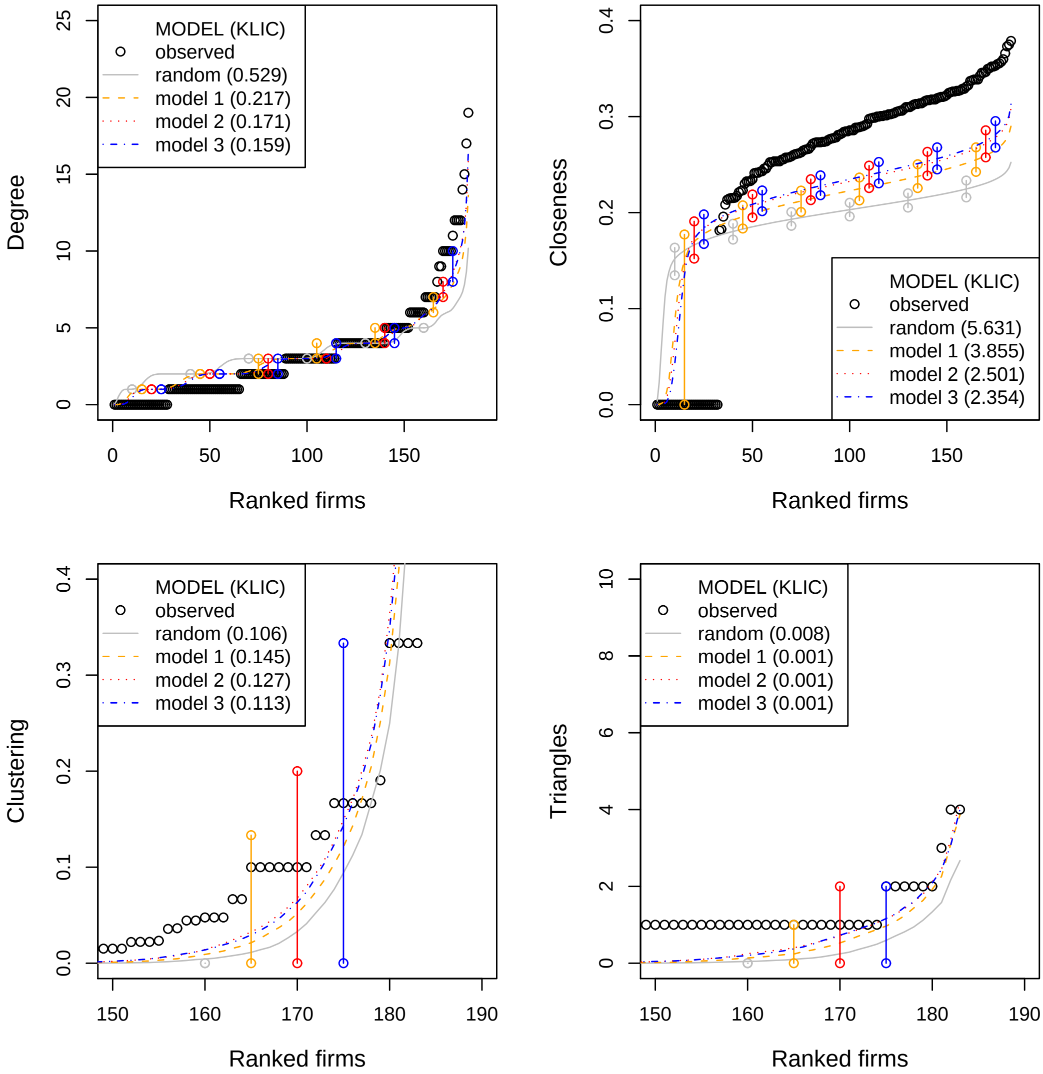

Figure B.1: *Observed and expected network measure distributions - restricted sample. Black circles are observations, lines give the average over 1000 simulations, circles connected by vertical lines indicate 90%-confidence intervals. KLIC compares probability masses according to the following cutpoints: degree (1, 2, 3, 5), closeness (0, 0.258, 0.287, 0.317), clustering (0, 0.015, 0.041, 0.1, 0.167), triangles (1, 2).*

tion', and 'overlap'. The analysis in the main text presented results of the overlap measure. All three measures are based on technological patent classes and we use the international patent classification (IPC). Patents are ascribed to IPC classes by the examiner in the patent office. The general idea is that a firm reveals its technological specialization by patenting in certain technological patent classes. The three distance measures use this information differently: overlap measures to what extent two firms patent in the same patent classes (see section 3.4.2). cRTA measures the similarity of specialization profiles, calculated with respect to the overall industry. Uncentered correlation simply correlates two vectors where each vector contains the number of a firm's patents in each IPC class. For use of these measures in prior literature see discussion when overlap is introduced, section 3.4.2, and the sensitivity analysis, section 3.5.2. The measures are calculated as follows:

$$overlap_{ij} = \frac{|IPC_i \bigcap IPC_j|}{|IPC_i \bigcup IPC_j|},$$

where IPC_i is the set of IPC, in which firm i had at least one patent applications and $||$ denotes the size of the set. Correlated revealed technological advantage (cRTA) is calculated in several steps (see e.g. Cantwell and Colombo, 2000). The revealed technological advantage (RTA_{ik}) of firm i in technological class k is firm i's specialization in class k relative to the average specialization in the industry, i.e.

$$RTA_{ik} = \frac{P_{ik}/\sum_k P_{ik}}{\sum_j P_{jk}/\sum_{jk} P_{jk}}$$

where P_{ik} is the number of patents firm i has in class k. This is done for each technological class to derive the RTA vector of firm i, i.e. $(RTA_{i1}, \ldots, RTA_{ik}, \ldots, RTA_{iK})$. Finally, cRTA is Pearson's correlation coefficient of the RTA vectors of two firms. The uncentered correlation of the IPC vectors of two firms is simply,

$$uncCorr_{ij} = \frac{\sum_{k=1}^{K} P_{ik}P_{jk}}{(\sum_{k=1}^{K} P_{ik}^2)^{1/2}(\sum_{k=1}^{K} P_{jk}^2)^{1/2}}$$

where P_{ik} is the number of patents firm i has in patent class k (see e.g. Jaffe, 1986). Uncentered correlation is different to Pearson's correlation in that vectors are not centered for calculating the angle of the vectors and, therefore, uncentered correlation remains between 0 (distant) and 1 (close) for vectors with only positive entries.

Alliance formation Table B.4 compares the estimation results for alternative specifications. Estimations based on the distance measure cRTA suggests that firms with similar specialization profiles attract each other since proximity measured by cRTA is positive and significant (see row 'proximity', column 'cRTA'). The square of cRTA however is not significant (proximity^2, third column). Thus, the cRTA model finds a positive effect of technological proximity on alliance formation but does not confirm the hypothesized curvilinear shape of the benefit-distance function. The measure *unc-Corr* does not find a significant effect of technological distance on alliance formation (fourth column). In sum, we find that not all distance measures attest to the effect of technological distance on alliance formation. The measures which do find a benefit-distance effect suggest that alliance formation is beneficial especially for firm-pairs which are close in technological space.

Table B.4: *Random effects logit models of alliance formation (jointtech) - alternative proximity measures* [a]

	Model 2	Overlap	Corr. RTA	UncCorr.
Intercept	-7.78***	-8.37***	-7.95***	-8.03***
	(0.364)	(0.422)	(0.375)	(0.425)
Proximity	–	4.12***	1.29***	0.91
		(0.987)	(0.370)	(0.739)
Proximity^2	–	-2.69**	-0.37	0.08
		(1.032)	(0.63)	(0.706)
SumLnPC	0.21***	0.11***	0.2***	0.16***
	(0.026)	(0.032)	(0.026)	(0.028)
AbsDiffLnPC	0.09**	0.21***	0.1**	0.13***
	(0.033)	(0.042)	(0.034)	(0.035)
AbsDiffLnEmpl	0.2***	0.21***	0.21***	0.2***
	(0.029)	(0.03)	(0.029)	(0.029)
SumLnEmpl	0.04*	0.05*	0.05*	0.05*
	(0.023)	(0.024)	(0.024)	(0.024)
σ^2 [b]	0.35	0.38	0.35	0.44
	(0.097)	(0.099)	(0.099)	(0.101)
AIC	3208.87	3186.22	3186.29	3188.7

[a] N=20910 firm-pair observations from crossing 205 firms; standard errors in brackets; *,**,*** signify 5%, 1% and 0.1% rejection levels of significance.

[b] The estimate of random effects variance follows a log-normal distribution and are therefore strictly positive.

Ego-network structures Table B.5 gives the correlation coefficients of observed and expected network measure distributions based on the estimates in table B.4. Overlap and cRTA improve predictions of model 2 which includes only size information (firm size and patent portfolio size). However, each improves significantly another aspect of the firm's ego-network. Whereas overlap improves significantly predictions of degree, cRTA improves triangles significantly. Uncentered correlation (uncCorr), with insignificant coefficients in the estimation, predicts closeness worse and triangles better than the benchmark, model 2. In sum, we find that distance measures which have been estimated to be significant improve predictions on ego-network structures relative to models which include only information on the size of the firm and the size of the patent portfolio.[2]

Table B.5: *Pearson's correlation of observed and expected firm ego-network characteristics - alternative proximity measures* [a]

		Model 2	Overlap	Corr. RTA	UncCorr.
Degree	r_m [b]	0.62***	0.64***	0.62***	0.62***
	$P_{m=model2}$ [c]	–	0.024	0.170	0.148
Closeness	r_m	0.29***	0.32***	0.30***	0.26***
	$P_{m=model2}$	–	0.222	0.369	1.000
Clustering	r_m	-0.03	0.00	-0.07	0.03
	$P_{m=model2}$	–	0.436	0.106	0.084
Triangles	r_m	0.30***	0.33***	0.37***	0.34***
	$P_{m=model2}$	–	0.130	0.001	0.110

[a] Expectations are based on estimates of the random firm effects model in a monte carlo approach with 1000 draws.
[b] r_m denotes the correlation coefficient; *,**,*** signify 5%, 1% and 0.1% significance level of zero correlation.
[c] $P[r_m = r_{m-1}]$ is rejection level of the null hypothesis that correlation coefficients of models m and $m-1$ are equal.

[2] Tests for the null hypothesis that correlation coefficients for two models are equal are based on Williamson's test statistic for dependent correlation coefficients as described in Steiger (1980, p.246); all tests are one-sided.

Global network structures Figure B.2 visualizes expected and observed network measure distributions for alternative specifications. Predictive power of all three distance measures is obviously very similar. Differences in the KLIC are low and attributable to the discretization of expected distributions.

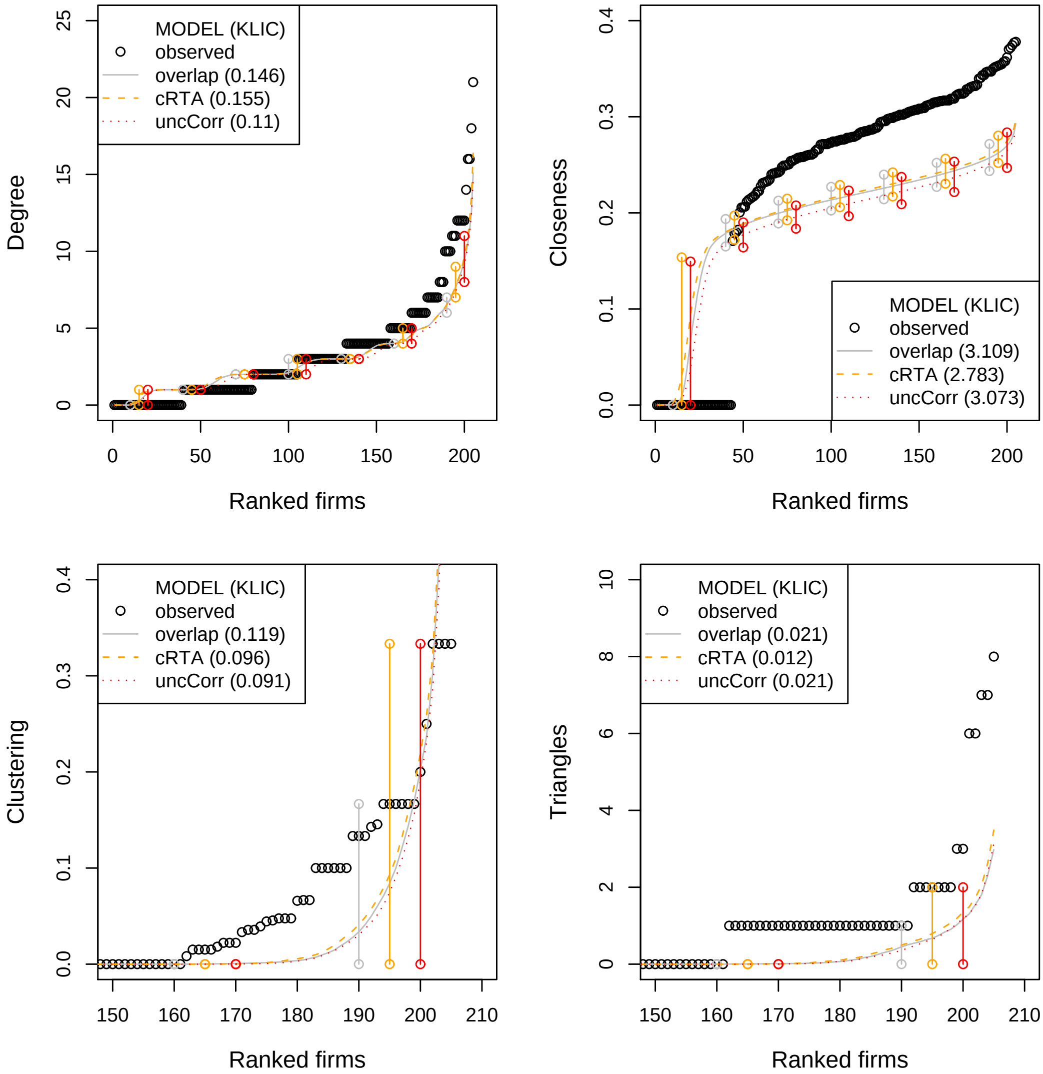

Figure B.2: *Observed and expected network measure distributions - restricted sample. Black circles are observations, lines give the average over 1000 simulations, circles connected by vertical lines indicate 90%-confidence intervals. KLIC compares probability masses according to the following cutpoints: degree (1, 2, 3, 5), closeness (0, 0.258, 0.287, 0.317), clustering (0, 0.015, 0.041, 0.1, 0.167), triangles (1, 2).*

CHAPTER 4

Technological and Social Effects on Network Formation

4.1 Introduction

This chapter compares two determinants of R&D networks: the technological space and the social network of prior alliances. The previous chapter confirms that the firms' technological position affects the pairwise formation of research alliances which in turn influences higher-level network structures. The social network perspective argues for the influence of the network structure on pairwise alliance formation. Whereas technological factors induce alliance formation, social factors enable and guide alliance formation. Both are important. How they relate to each other is an intriguing question which we tackle in this chapter.

For the empirical analysis, we use the same sample of the pharmaceutical industry and follow the same analysis strategy as in the previous chapter. Social network factors are estimated on the prior network of alliances. First, we estimate technological and social network factors on pairwise alliance formation. These estimates are then used to make predictions of both the firms' ego-networks and the global network structure. Technological and social network explanations yield similar results. Both are significant for dyad formation and relevant predictors of firms' ego-networks but do not predict global network structures very well. Models of pairwise alliance formation which include social network factors tend to better fit network structures. However, the sensitivity analysis shows that social network factors are susceptible of spurious path dependency. Therefore, explanation of research alliances and networks is better sought in technological factors.

The chapter is structured as follows. Section 2 gives a background on the literature and develops the research questions. Section 3 provides a statistical analysis on how the network of prior alliances relates to the current research network. Section 4 presents the results of the separate and joint estimation of technological and social network effects. Section 5 discusses the results, addressing the potential relevance of measurement errors and network endogeneity. The final section concludes.

4.2 Background Literature and Research Questions

4.2.1 Social Network Effects

The discussion in the previous chapter highlights the need to access complementary technological resources as the main motivation for joint research. The alliance partner needs to provide complementary resources and needs to have a self-interest in the partnership. However, finding the right partner might prove difficult and, given the right partner has been found, more obstacles need to be overcome. Two firms are separate legal entities with diverging interests. Thus, they might encounter appropriability problems (e.g. leakage of knowledge) and moral hazards (e.g. opportunistic behavior) (Williamson, 1991). Because during an alliance unforeseen, non-contractible events arise, partnering firms need to trust each other (Gulati, 1995a). In addition, partnering firms face organizational problems. They need to decompose tasks, coordinate inter-firm communication and adapt to fit their processes together (Doz, 1996; Gulati and Singh, 1998). Inefficient coordination may become costly and time consuming. In the worst case, lack of appropriate coordination makes alliances fail (Doz, 1996).

The important insight from economic sociology (Burt, 2001; Coleman, 1986; Granovetter, 1985) and organizational learning (Cohen and Levinthal, 1990; Kogut and Zander, 1992) is that alliances take place in a social and historical context (Hemphill and Vonortas, 2003). This guides partner search, mitigates appropriability problems, moral hazard as well as the coordination problem.

Firms are directly and indirectly connected through business and personal relationships. This creates a social network in which firms are embedded. The firm's social network performs several important functions (Granovetter, 1985). It provides information, allows for inter-organizational learning and generates norms of behavior. Granovetter (1985) argues that the structure of the social network is influential because social mechanisms act locally through actual relationships. For example access to personal information is not the same for all firms but is provided to firms via their relationship to specific other firms. Furthermore, social mechanisms are moderated by local configurations of the social network (Coleman, 1988). For example common norms of behavior are enforced through coordinated action of densely connected agents. Therefore, the social network structure and the position a firm takes in the network determine the firm's constraints and opportunities for economic action.

The effect of social structure on firm behavior tends to be couched in terms of three types of embeddedness: relational, structural and positional embeddedness (Gulati and Gargiulo, 1999).

Relational embeddedness addresses the direct relationship of two specific firms. Through ongoing interactions, firms learn about conduct, capabilities and needs of the partnering firm (Gulati, 1995a). This is valuable information for future partner search and raises the awareness for collaboration opportunities with that particular firm. In addition, social relationships develop, which creates a common understanding and norms of behavior. Firms build routines for interaction and shared codes of understanding. This decreases coordination costs and increases the probability of success (Powell et al., 1996; Ring and Ven, 1994). Furthermore, anticipation of alliances in the future enforces good behavior (Gulati, 1995a). All points mentioned, i.e. knowledge about the partner, social relationships, common understanding and anticipation of future alliances, create trust among the partners, which is a crucial ingredient for collaboration.[1]

Structural embeddedness takes into account the local network structure in which a firm is embedded. The local network results from all partners of the focal firm and all their relationships. First consider only relationships among the partners of the focal firm. When the partners are closely connected among each other, the focal firm and its partners form a cohesive group. Coleman (1988) argues that closed social structures facilitate joint action of individuals to make norms effective. Imagine our focal firm behaves opportunistically with one partner. Other partners will be informed about this misbehavior through their contacts in the group with the effect that the (local) reputation of the focal firm is damaged. In this way, firms in cohesive groups can trust each other because good behavior is enforced. For the formation of alliances the effect of referrals has been found to be important too. Two firms having no direct relationship might be referred to each other by a common partner. Because a common partner has personal experience with both firms, she knows about their conduct, needs and capabilities (Gulati and Gargiulo, 1999).

Positional embeddedness describes the position of the firm within the overall network. The position may be described in terms of its centrality in the network. Since the network structure directs information, firms in more central positions have access to more timely and more accurate information (Owen-Smith and Powell, 2004). Thus, they gain better information about more potential partners and are able to seize opportunities for alliances (Gulati and Gargiulo, 1999). In addition, central firms having many alliances are more visible in the industry. Successful alliances in the past build a reputation as a reliable and capable partner (Gulati and Gargiulo, 1999). Finally, alliances with central firms may also be sought because they enhance the legitimacy of the partnering firm (Oliver, 1990).

[1] Trust resulting from past interaction is also called knowledge-based trust, trust resulting from future expectations deterrence-based trust (Gulati and Singh, 1998).

We summarize the discussion of social network effects. Empirical studies have found that alliance formation is moderated by the structure of the prior network of alliances. We may conveniently distinguish three kinds of social embeddedness: relational, structural and positional embeddedness. Two firms are relationally embedded, when they had a relationship in the past. The effect of prior ties on alliance formation has been found to be significant in virtually all studies. Structural embeddedness takes into account the local network of a focal firm. When two firms have many common partners, they are highly structurally embedded. Many but not all studies found that having common partners increases the probability for two firms to form an alliance. One reason is the referrals from common third parties. Positional embeddedness describes the role of a firm in the overall network. This is most commonly done by measures of centrality (degree and eigenvector) which, again, are found to be significant in most studies.

4.2.2 Technological and Social Network Effects

This section joins prior empirical literature on technological and social network effects to develop the research questions. The discussion of prior literature is organized according to the three levels which we follow in our empirical analysis. The levels are i) alliance formation between firm-pairs, ii) ego-network structures, and iii) global network structure.

Alliance formation Empirical research on how social embeddedness affects pairwise alliance formation is extant. Relational, structural and positional embeddedness has been found to significantly affect alliance formation in various industries.[2] The typical strategy in this literature is to introduce social network statistics in a binary choice model, such as logit or probit, where the outcome is whether or not a specific firm-pair forms an alliance. All studies find a strong positive effect of relational embeddedness in prior ties. Structural embeddedness typically is introduced via the number of common partners of a firm-pair given they do not have a direct relationship (Gulati, 1995b; Gulati and Gargiulo, 1999; Rosenkopf and Padula, 2008; Hallen, 2008). This measure is designed to catch the effect of referrals. It has been found to be positive significant in all studies, except Rosenkopf and Padula (2008) who investigate the mobile communication industry. Positional embeddedness often is indicated by the agents' centrality in the network. Specifically eigenvector centrality (Gulati and Gargiulo,

[2](Gulati, 1995b; Gulati and Gargiulo, 1999) investigate the new materials, industrial automation and automotive sectors in a (panel data); (Powell et al., 2005) the alliance network of biopharmaceutical firms (panel data); (Rosenkopf and Padula, 2008) the mobile communications industry (panel data); (Chung et al., 2000) underwriting syndicates in the banking sector (cross-section analysis) and (Hallen, 2008) corporate investments on start-ups in various industries (cross-section analysis). None of these studies focuses on research alliances.

1999; Rosenkopf and Padula, 2008) and degree centrality (Gulati, 1995b; Powell et al., 2005) have been used and found to be significant.

Whereas the empirical literature on alliance formation in general focuses on social network effects, the empirical literature which considers explicitly the formation of research alliances focuses on technological explanations (see also the discussion in the previous chapter, section 3.2). However, the arguments put forward by knowledge economics and social structure thinking are complementary to each other. Access to complementary knowledge induces, whereas social embeddedness enables the formation of research alliances (Eisenhardt and Schoonhoven, 1996). Yet, no empirical work on pairwise alliance formation discussed above focuses on the relationship of technological and social network effects. Technological factors often are only controlled for by rough proxies. For example Gulati (1995b) controls for interdependence by (joint) industry affiliation of the firms. The relative and joint relevance of technological and social factors on the decision to form an alliance is therefore an open question.

This chapter investigates the intriguing question whether one effect dominates the other or can be a statistical proxy for the other. For strategic management this is of high interest. Empirical findings on the strong structuring effect of past alliance networks lead to the perception that alliance formation is highly path dependent. Recently, active networking has been emphasized in order to break out of the high path dependency of network formation and to achieve outperforming network positions (Gilsing et al., 2007; Ozcan and Eisenhardt, 2009). A different course of action would be suggested if technological characteristics turn out to be the main determining factors.

Another question tackled in this chapter is to what extent social embeddedness moderates technological effects. The concept of absorptive capacity states that for joint knowledge production, firms need to be cognitively close. This leads to the proposition that two firms being close in technological space are likely to form a research alliance. However, absorptive capacity is broader in its meaning. It also implies that a shared language and adapted organizational processes are necessary (Cohen and Levinthal, 1990). The literature on organizational learning argues that firms might adapt their languages and routines in prior alliances and interaction within a cohesive group of firms (for example Gulati, 1995a; Kogut and Zander, 1992). Therefore, it might well be that social embeddedness alleviates the necessity of technological proximity. This would imply that two firms which face low organizational risk might be able to bear higher technological risks by combining more distant technological knowledge. A similar implication has been investigated by Gilsing et al. (2008). They found a trade-off between network centrality and technological distance for explorative technological search by firms in the chemicals, automotive and pharmaceutical sectors. Because there might also be a trade-off between technological and social proximity in the decision with whom to partner, we introduce interaction effects of social and technological distance in the regression.

Ego-network structures Following the analysis strategy in the last chapter, we are not only interested in what drives pairwise formation of research alliances but, in addition, how the pairwise alliance formation process influences higher-level network structures. As before we investigate the implications of pairwise alliance formation both on the firm's ego-network structure and on the global structure of the research network.

Prior analyses of the effect of social embeddedness on firm alliance behavior typically remains at the firm level. One prevailing line of research is to consider the firm's embeddedness in the social network as a source of value creation as it provides opportunities for interaction among firms. In this view, social embeddedness determines the social capital of the firm. In general, social capital is assumed to be higher for firms that are more embedded in the social network. Social capital has been measured by degree centrality (Ahuja, 2000) but also via the contribution of the firms' (cohesive) group to the overall structure of the alliance network (Shan et al., 1994; Walker et al., 1997).[3] In either case, social capital has been found to increase the number of commercial ties of biotechnology firms (Shan et al., 1994), research joint ventures of chemical companies (Ahuja, 2000) and any type of alliance for biotechnology firms (Powell et al., 1996).

The study of Ahuja (2000) is especially relevant to us as he combines the symbiotic interdependency argument of the resource-based view with the social capital argument of structural sociology. He subdivides the firm's resources into technological, commercial and social capital. According to the author, a firm is attractive to potential alliance partners if it is able to offer either technological or commercial resources needed by the partner. Thus, mutual access to complementary resources provide the inducement to form an alliance. The third type of capital, social capital, refers to embeddedness in the social network (Coleman, 1988). Invoking the social network arguments discussed above, Ahuja proposes that firms which are highly (positionally) embedded in the network have higher incentives and more opportunities to form alliances. He analyzes a longitudinal sample of agreements among the 100 largest firms in the chemicals industry over a ten year period. Agreements include research joint ventures and research alliances. Technological capital is measured as the number of patents applied for within the last four years, commercial capital is proxied by the assets of the firm, and social capital is measured as the firm's number of past technological agreements. The number of the firm's past commercial alliances is used as a control. A poisson panel model estimates the effect of one-year-lagged variables on the number of research agreements formed by the firm in a given year. The estimation results confirm that each type of capital by itself increases the propensity of a firm to engage in technological agreements. A comparison of the effects is accomplished by estimating the effect of a one standard deviation increase in each of the three forms

[3] This measure mixes structural embeddedness and positional embeddedness.

of capital on the 'average' firm. The estimates imply that increasing technological, commercial and social capital by one standard deviation increases linkage formation by 20%, 50% and 10% respectively. In addition, the author finds a moderating effect between technical and commercial capital. If both is high, alliance rate decreases. The explanation put forward is the lower necessity to access either kind of complementary resource.

Taking the same theoretical stand-point, one contribution of this chapter is to broaden the perspective. Ahuja (2000) highlights the relevance of social and technological factors but includes only the size dimension, i.e. the number of alliances and patents respectively. Our study is broader in that we include also the structural dimension, i.e. the local structure of the firm's ego-network and the technological-distance relationship in technological space.

Global network structures Although many empirical studies investigate how the social network structure influences firm-pair alliance formation, little is known on their relevance in the network formation process. Because relatively few potential alliances actually realize, estimated errors are considerable and a large part of alliance formation between firm-pairs remains unexplained. Therefore findings on the significance of social network effects on alliance formation do not give us a clear perception of the extent to which the past network determines the future network. Thus, one might be tempted to state that actually no empirical study exists which explicitly investigates social network effects on the network level.

Cowan et al. (2007) model theoretically the formation of a network formed by joint knowledge production among heterogeneous agents. The partnering decision of firms depends on the complementarity of their knowledge endowments but also on their relational and structural embeddedness in the network of prior alliances. When two firms already had a successful alliance learning effects lead to higher probabilities of success in future alliances. Furthermore, referrals affect positively the mutual perception of two formerly unrelated firms. The model has been found to produce realistic networks, i.e. networks with the small world properties of short average distance and high clustering. However, a more recent theoretical model shows that real-world like networks might also be created solely through technological effects (Cowan and Jonard, 2009). To what extent social and technological factors determine the global network structure is an empirical question which we tackle in the following.

4.3 Empirical Methods

The empirical analysis of this chapter builds on the previous chapter. The sample, measures and estimation strategy are as in the previous chapter and only extended to include social network variables as independent variables. In order to avoid duplication of information, in the following only the most relevant information is briefly given and the reader is referred to the previous chapter for detailed explanations.

4.3.1 Sample

As in the previous chapter we work on a sample of the 250 most active firms in the pharmaceutical industry. The phenomenon which we aim to explain is the research network among the sampled firms which has been formed between the years 2001 and 2006 (inclusive). The technological position of firms is measured with patent data. The patent data are obtained from a period previous to the time period of the research network, i.e. between the years 1995 and 2000. To control for size effects, we also collected the firms' number of employees for the time shortly before the research network actually formed; mostly for the year 2001.

The sample is extended by the network of prior alliances. The prior network is the collection of all (bio-)pharmaceutical alliances between 1995 and 2000 (inclusive) between all actors in the industry. It is built using all types of alliances because the arguments for social network effects are not specific to any particular kind of inter-firm relationship. Furthermore it contains all actors of the industry in order to capture the embeddedness of the sampled firms in the overall network of alliances. Thus, in the analysis we use snapshots of two networks both formed within six years. The prior network, built between 1995 and 2000 containing all types of alliances between all actors, yields social network measures which are used to explain the research network of the sampled firms, built between 2001 and 2006. Both networks are constructed from data of the same data base, i.e. the CGCP data base.

The sample consists of 250 firms. 38 firms have zero or missing patent assignments, 14 firms have missing employee information and 45 firms have neither patent nor employee information assigned. In total, for 205 firms, which is 82% of the sample, patenting and employee information is given. This sample has been used for the analysis in the previous chapter.

For 68 firms out of the 205 focal firms, no alliance in the prior network is registered in the database. From the set of firms without registered alliances, we chose a random control sample of ten firms and searched for public agreements on the firms' websites, their public releases, and other alliance databases. For eight out of ten firms, we found alliances for the respective time period. However, the number of alliances per firm in the control sample is small (mostly one, up to four alliances). Furthermore, the group of 68 firms without prior alliance activity has low centrality in the global network formed in the years 2001 and 2006. The fact that no sudden change in the alliance activity occurred implies that missing alliance data does not necessarily create a large bias. Nevertheless, the robustness analysis (Appendix C.4) addresses this issue and presents additional results on a restricted sample which excludes firms without prior alliances. In the following we present data and results of the full working set, with all

205 focal firms included; the same working set as in the previous chapter.

4.3.2 Measures

The dependent variable at the firm-pair level is 'joint technological agreement' (*joint-tech*), which indicates whether or not a firm-pair had at least one research alliance between the years 2001 and 2006. In addition, we aim to explain the ego-network of the firm and the global structure of the research network which formed in the years 2001 to 2006. Both are described with the four network measures degree centrality, closeness centrality, clustering coefficient and number of triangles (in short *degree*, *closeness*, *clustering*, and *triangles*).[4]

Independent variables include those used in the previous chapter (see chapter 3, section 3.4.2 for explanation or table 4.1 for a summary). Notably information on the technological position of the firm as measured by its patenting between the years 1995 and 2000. This includes the technological proximity between the firm-pair, measured by overlap and the information on patent portfolio sizes, captured by the sum as well as the absolute difference of the log-transformed patent counts (*sumLnPC*, *absDiffLnPC*). In order to control for the size of the firm we construct similarly the sum and the absolute difference of the log-transformed number of employees of the firm-pair (*sumLnEmployee*, *absDiffLnEmployee*).

The independent variables introduced in this chapter aim to capture the structuring effect of the prior network of alliances, formed in the years 1995 to 2000. Following the seminal study of Gulati and Gargiulo (1999), we construct one network measure for each type of embeddedness from the network of prior alliances. Two firms are relationally embedded when they had an alliance in the prior network. This is indicated by *prior ties*. Structural embeddedness takes into account the local network of the focal firms. Two firms which have many common partners are highly structurally embedded, which we indicate by the number of *common partners*. In order to capture the effect from referrals *common partners* is set to zero if the firm-pair has *prior ties* (see also Gulati and Gargiulo, 1999, p.1463). Positional embeddedness refers to the position of the focal firm in the global network. As Ahuja (2000), we indicate positional embeddedness with the firm's degree centrality, i.e. the number of alliances in the prior network. In order to introduce this information as independent variable in a model of firm-pair alliance formation, we need to construct a relational variable out of the degree of two firms. Similar to the patent counts and firm size, the degree information

[4]The network measures are assumed to be relevant for various reasons, depending on the theoretical framework. For example a high degree centrality, i.e. many alliances, might give a firm high reputation in the industry. High closeness centrality, i.e. short network paths to all other firms in the network, might give a firm fast access to information. High clustering and many triangles might enforce trust by enabling joint action. Please see the discussions when the network measures are introduced in chapter 2, section 2.4

is captured by taking the sum and the absolute difference of the log-transformed degree of firm i and j (*sumLnDegree*, *absDiffLnDegree*). These and all other variables used in this study are summarized in table 4.1.

4.3.3 Statistical Analysis

As a first step of the data analysis, this section compares the position of the 205 focal firms in the prior network of alliances with their positions in the current network of alliances. Descriptive statistics show that these firms kept their network positions over time. This implies that the network has some inertia and, therefore, path dependency due to social network effects qualifies as a possible explanation. In particular it is shown that the three types of embeddedness, i.e. positional, structural, and relational embeddedness, potentially cause structural stability of the alliance network.

Prior and Current Network The 205 focal firms linked to each other in 339 dyadic research alliances between the years 2001 and 2006. This is the research network which we aim to explain. The research network of the focal firms is part of the global pharmaceutical network. The global network includes around 5000 firms which are connected by 7000 alliances for diverse purposes. The main component of the global pharmaceutical network, i.e. the largest connected subgraph, connects over 80% of the firms.

As the prior network of alliances we denote the global pharmaceutical network which has been formed between the years 1995 and 2000. The structure of this network might partly explain the research network which formed in the following time period. The prior network of alliances consists of 1404 firms, linked by 2256 alliances. The majority of firms (85%) is connected within the main component.

Positional embeddedness Table 4.2 compares the average position of sampled firms to the average position of all firms in the prior and current global network. We sampled the 250 firms which have most alliances in the current global pharmaceutical network. Naturally, they are central actors in the current global network. Sampled firms have much higher degree than the average and higher closeness (see table 4.2, column 'current global network'). Their network position in the core of the network makes them participate in many triangles. This also yields a high clustering coefficient compared to the average firm in the network. A social network explanation of the firm's central position in the current global network would be that these firms occupied favorable positions in the prior network giving them many opportunities for alliance formation. Indeed, our sampled firms took central positions already in the prior global network (1995-2000) (see table 4.2, column 'prior global network'). Their average number of alliances is about twice the population average. Also in terms of closeness centrality, sampled firms are (slightly) more central in the prior network.

Table 4.1: *Variables of alliance and network formation* [a]

Variable Label	Unit of Observation	Description
Dependent Variables (2001-2006)		
Jointtech	Dyad	Indicates a joint technological agreement between a firm-pair
Degree centrality	Firm/Network[b]	The firm's number of alliances
Closeness centrality	Firm/Network	One divided by the firm's average path length to all other firms
Clustering coefficient	Firm/Network	How close the firm's neighborhood is to being fully connected
Number of triangles	Firm/Network	The number of alliances among neighbors of the firm
Independent Variables (1995-2000)		
Prior ties	Dyad	Indicates whether a firm-pair had a prior alliances
Common partners	Dyad	Number of partners common to both firms, zero if firm-pair has prior ties
AbsDiffLnDeg	Dyad	Absolute difference of the firms' log-transformed degree
SumLnDeg	Dyad	Sum of the firms' log-transformed degree
Overlap	Dyad	Number of IPC classes covered jointly by both firms divided by the number of IPC classes covered by at least one firm
Overlap^2	Dyad	The square of overlap
AbsDiffLnPC	Dyad	Absolute difference of the firms' log-transformed number of patents
SumLnPC	Dyad	Sum of the firms' log-transformed number of patents
AbsDiffLnEmployees	Dyad	Absolute difference of the firms' log-transformed number of employees
SumLnEmployees	Dyad	Sum of the firms' log-transformed number of employees

[a] Prior ties, common partners, absDiffLnDeg, and sumLnDeg are introduced in this chapter, all other variables are introduced in the previous chapter, section 3.4.2.

[b] The network structure is described by the distribution of network measures over sampled firms.

Table 4.2: Network positions in the prior and current network

	Prior Global Network (1995-2000)		Current Global Network (2001-2006)	
	Population	Sampled Firms	Population	Sampled Firms
Degree	3.2	6.5	2.9	20.5
Closeness	0.23	0.26	0.20	0.25
Clustering	0.020	0.025	0.008	0.026
Triangles	0.4	1.4	0.28	5.3

In total, the 205 focal firms have been central in the prior network (1995-2000) and, when the overall alliance activity tripled, these firms became even more central in the current network (2001-2006). The fact that the focal firms strengthened their central network position relative to the rest of the population might indicate the existence of the social network effect termed accumulated advantage (also called the rich-get-richer effect).[5] Accumulated advantage fosters network centralization because it means that firms with more links have a higher propensity to attract further links during network growth. In the context of alliance networks explanations for the existence of such an effect have been for example reputation and signaling effects. The fact that a firm has many alliances signals that this firm is a valuable and trustable partner. Firms with many alliances enjoy high reputation in the industry and connecting to such firms also increases the reputation of the alliance partner.

Comparison of the focal firms' positions relative to each other further supports the existence of an accumulated advantage effect. Pearson's correlation coefficients of the sample firm's degree in the prior global network (1995-2000) is highly correlated with their degree in the current research network (2001-2006), with a correlation coefficient of 0.62, below the 1% significance level. Also closeness centrality measured on the two networks obtains a high correlation coefficient of 0.4 below the 1% significance level.[6] This means that the ranking among the focal firms with respect to their centrality remained stable. In sum, our observations on positional embeddedness, i.e. degree and closeness centrality, supports the network path dependency as well as the accumulated

[5] The accumulated advantage effect became famous for a theoretical model of network formation. In the theoretical model of Barabási and Albert (1999), each time step a new node is added to the network and connects to nodes already in the network. The probability to connect to a certain node is proportional to the number of links of the node in the network. The model attracted considerable attention because it has been shown that this simple process is able to produce degree distributions according to the power law; a feature of the global network structure shared by many different kinds of real-world networks.

[6] Correlation between the prior global network (1995-2000) and the current global network (2001-2006) are similarly high and of same significance for degree and closeness.

advantage arguments.

Structural Embeddedness Whether structural embeddedness may affect future network formation is reflected in the structure of the firm's ego-networks. The average clustering coefficient in the global current network is much higher than would be expected in a random network of the same size and density (0.01 vs. 0.0004). High clustering in the network might be caused by referrals. A referral effect is when two firms have no direct prior relationship but form an alliance after having been introduced by a common alliance partner. Each referral closes a triangle. Because sampled firms are involved in an increasing number of triangles (see table 4.2, row 'triangles'), they might well be influenced by referrals, captured by the variable *common partners* in the econometric analysis.

Clustering also provides some evidence on network inertia. Clustering of the sampled firms in the prior global network (1995-2000) and in the current research network (2001-2006) are considerably correlated with a Pearson's correlation coefficients of 0.14 being below the 5% level of significance. For triangles, we obtain a correlation coefficient of 0.31 below the 1% level of significance. This suggests that the structure of the focal firms' ego-networks remained rather stable and firms stayed over time in more or less densely connected regions of the network.[7]

Relational Embeddedness Finally, relational embeddedness, measured by *prior ties*, potentially explains alliance formation. Table 4.3 shows that *prior ties*, measured on the prior network, is significantly correlated with research alliance formation (*joint-tech*). Theoretical explanations for the positive effect of prior collaborations are among others organizational adaptation and building of trust.

Summary and Remark To summarize, descriptive statistics suggest that positional, structural and relational embeddedness may affect network formation. Furthermore, firms kept their relative network position in a growing and centralizing network. This regularity gives rise to the social network thesis that the network of alliances is self-reproducing due to social network effects.

However, an alternative explanation is that stable exogenous factors cause the stability of network configurations. If firms form alliances due to their relative properties, such as complementary knowledge, then persistence of the firms' properties leads to

[7] It might be noticed that clustering among the focal firms in the current research network is low; similar to expected clustering of a random graph of same size and density (0.02 vs. 0.013). The reason might be in the sampling procedure. Because firms have been sampled according to their degree centrality, local network structures are not respected and, therefore, the ego-network of the focal firms is not complete in the current research network. Nevertheless, when connections among focal firms result from third party referrals this is going to be reflected in the estimation because the global prior pharmaceutical network is used to calculated the number of *common partners*.

stable network structures. In principle all resources defined within the resource based view may qualify; they are stable, slowly accumulating and practically not tradeable. In particular, the previous chapter showed that the technological space provides a structure which is reflected in the research network. The econometric section compares the technological and social structure explanation.

Table 4.3 summarizes the correlation between dependent and independent variables which are taken into account in the model of alliance formation. Stated significance levels for the correlation coefficients are probably too low because the covariance of error terms between observations is not taken into account. Nevertheless at least two things might be noted. Firstly, variables capturing size aspects of the firm-pair are strongly correlated. These are the sum of the firm-pair's joint patent-portfolio (*sumLnPC*), their joint degree centrality (*sumLnDeg*) and the sum of firm size (*sumLnEmpl*). Secondly, we also observe some correlation among variables which capture structural aspects of the social network and technological space. More specifically, the social network variables *common partners*, *prior ties* and the technological variable *overlap* are significantly correlated. Therefore we might expect that our measures of the social space and the technological space provide similar information for alliance formation. If both types of variables proxy the same factors of alliance formation, coefficients of joint and separate estimations are going to differ.

4.3.4 Estimation Strategy

The principle steps of this analysis are the same as in the previous chapter, described in section 3.4.4. In the first step, a logit model of pairwise alliance formation is estimated. The logit model includes firm specific effects to account for dyadic interdependence. The estimates of random and fixed firm specific effects are compared using a simplified Hausman test. In the second step, the estimates of the logit model are used to predict i) the firms' ego-network structures and ii) the global network structure. Expectations are derived from 1000 simulations. The number of simulations suffices to obtain the same results in different simulation studies. Comparison of predictions and observations in the sample informs us on the explanatory power of the variables introduced in the logit model of dyadic decision making.

Estimation results are obtained under the assumption of no measurement errors and no spurious path dependency. These issues are discussed in the sensitivity analysis section. The potential upward bias of social network effects due to spurious path dependency is addressed by estimations which distinguish prior research alliances from prior non-research alliances. Another issue is that some focal firms are not embedded in the prior alliance network. This might create a downward bias of social network effects, which we address in a separate estimation on a restricted sample.

Table 4.3: Mean, standard deviations and correlations [a]

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10
Jointtech	(1)	0.02	0.13										
SumLnPC	(2)	8.77	2.94	0.09***									
AbsDiffLnPC	(3)	2.38	1.75	0.06***	0.14***								
Overlap	(4)	0.32	0.23	0.04***	0.57***	-0.37***							
Overlap^2	(5)	0.15	0.17	0.04***	0.51***	-0.35***	0.95***						
Prior ties	(6)	0.01	0.13	0.09***	0.08***	0.01	0.07***	0.06***					
Common partners	(7)	0.08	0.40	0.03***	0.22***	-0.03***	0.20***	0.23***	-0.02**				
SumLnDeg	(8)	2.43	1.68	0.10***	0.48***	0.12***	0.33***	0.31***	0.17***	0.38***			
AbsDiffLnDeg	(9)	1.33	1.04	0.02**	0.17***	0.21***	0.02*	-0.01	-0.04***	-0.10***	0.33***		
SumLnEmpl	(10)	13.11	3.41	0.07***	0.56***	0.23***	0.22***	0.23***	0.05***	0.17***	0.30***	0.14***	
AbsDiffLnEmpl	(11)	2.74	2.05	0.08***	0.16***	0.34***	-0.15***	-0.18***	0.04***	-0.05***	0.07***	0.10***	0.29***

[a] N=20910 firm-pair observations from crossing 205 firms; *,**,*** signify 5%, 1% and 0.1% rejection levels of significance.

4.4 Results

4.4.1 Estimation Results

Alliance Formation

Estimation Results Tables 4.4 and 4.5 present the results of the logit estimation. In table 4.4, model 1 is the base model which contains only firm size controls. Technological and social network effects are estimated separately in models 2 and 3 respectively and jointly in model 4. In addition, models 5 to 8 in table 4.5 include interaction effects between the technological-distance effect and variables of social embeddedness.

Comparing the overall fit of the models, we find that both the social network model (model 3) and the technology model (model 2) perform better than the base model, as the Akaike Information Criterion (AIC) decreases. The social network model (model 3) provides a better fit to the data than the technology model (model 2). Combining both explanations in model 4 improves the fit; but only slightly. Interaction terms in models 5 to 8 do not improve the model any more (see AIC in table 4.5).

Examining the coefficient estimates of the social network model (model 3) shows that *prior ties* positively affect alliance formation. Furthermore two firms with high degree are likely to form alliances as indicated by the variable *sumLnDeg* which is positive and significant. One interpretation of this result is that firms with high reputation tend to join for alliances. The other two social network variables are not significant. The number of *common partners* has no significant effect on the propensity of a firm-pair to form a research alliance suggesting that in this sample at least, referrals are not playing a large role in partner choice. Also *absDiffLnDeg* is insignificant, meaning that firm-pairs with large differences in their degree do not attract each other. This result may be partly due to the sampling of larger firms in the core of the network.

The positive effect of relational embeddedness, indicated by *prior ties*, is in accord with empirical findings in the previous literature. Also joint centrality of the firm-pair has been estimated to be positive (Gulati and Gargiulo, 1999, p.1470). With respect to the literature, it is remarkable that the number of *common partners* has no effects. All the studies in the literature section (section 4.2) found a significant positive effect of *common partners* except the study by Rosenkopf and Padula (2008) who investigate the mobile communication industry. A simple explanation for our result may be that referrals have no effect in our sample because firms from the core of the network know about each other very well.

The technological variables are all significant when estimated separately in model 2. When estimated jointly with social network variables, the coefficient of *sumLnPC* (joint size of the patent portfolio) becomes insignificant and coefficients of the other technology variables change only slightly with respect to standard errors. In particular, the inverse-U-shaped benefit-distance effect, i.e. *overlap* and *overlap*^{2}, is similarly strong and significant in both models. Social network estimates are similar in the

Table 4.4: *Random effects logit models of alliance formation (joint-tech), models 1-4* [a]

	Model 1	Model 2	Model 3	Model 4
Intercept	-7.23***	-8.37***	-7.29***	-7.94***
	(0.347)	(0.422)	(0.383)	(0.436)
Overlap	–	4.12***	–	3.21***
	–	(0.987)	–	(1.035)
Overlap^2	–	-2.69**	–	-2.44*
	–	(1.032)	–	(1.094)
SumLnPC	–	0.11***	–	0.03
	–	(0.032)	–	(0.034)
AbsDiffLnPC	–	0.21***	–	0.15***
	–	(0.042)	–	(0.044)
Prior ties	–	–	0.7***	0.7***
	–	–	(0.153)	(0.153)
Common partners	–	–	0	0.02
	–	–	(0.08)	(0.083)
SumLnDeg	–	–	0.45***	0.35***
	–	–	(0.044)	(0.05)
AbsDiffLnDeg	–	–	0.07	0.03
	–	–	(0.056)	(0.059)
SumLnEmpl	0.16***	0.05*	0.05*	0.03
	(0.019)	(0.024)	(0.022)	(0.025)
AbsDiffLnEmpl	0.23***	0.21***	0.21***	0.19***
	(0.026)	(0.03)	(0.027)	(0.031)
σ^2 [b]	0.35	0.38	0.39	0.39
	(0.095)	(0.099)	(0.102)	(0.102)
AIC	3287.05	3186.22	3105.1	3084.65

[a] N=20910 firm-pair observations from crossing 205 firms; standard errors in brackets; *,**,*** signify 5%, 1% and 0.1% rejection levels of significance.
[b] The estimate of random effects variance follows a log-normal distribution and are therefore strictly positive.

Table 4.5: *Random effects logit models of alliance formation (jointtech), models 5-8* [a]

	Model 5		Model 6		Model 7		Model 8	
Intercept	-7.95***	(0.439)	-8.03***	(0.448)	-8.64***	(0.599)	-8.02***	(0.518)
Overlap	3.08**	(1.057)	4.01***	(1.083)	7.28**	(2.597)	3.68*	(1.700)
Overlap^2	-2.19*	(1.137)	-3.5**	(1.172)	-6.76*	(3.260)	-2.9	(1.781)
SumLnPC	0.03	(0.034)	0.03	(0.034)	0.03	(0.034)	0.03	(0.034)
AbsDiffLnPC	0.15***	(0.044)	0.15***	(0.044)	0.14***	(0.044)	0.15***	(0.044)
Prior ties	1.2	(1.201)	0.67***	(0.157)	0.73***	(0.154)	0.69***	(0.153)
Common partners	0.01	(0.084)	0.29	(0.532)	0.01	(0.096)	0.02	(0.085)
SumLnDeg	0.35***	(0.050)	0.37***	(0.051)	0.58***	(0.138)	0.35***	(0.050)
AbsDiffLnDeg	0.03	(0.059)	0.02	(0.059)	0.02	(0.059)	0.09	(0.17)
Overlap · Prior ties	-0.15	(4.962)	–		–		–	
Overlap^2 · Prior ties	-1.61	(4.818)	–		–		–	
Overlap · Common partners	–		-1.88	(1.784)	–		–	
Overlap^2 · Common partners	–		1.93	(1.363)	–		–	
Overlap · SumLnDeg	–		–		-1.11*	(0.611)	–	
Overlap^2 · SumLnDeg	–		–		1.11	(0.688)	–	
Overlap · AbsDiffLnDeg	–		–		–		-0.29	(0.855)
Overlap^2 · AbsDiffLnDeg	–		–		–		0.28	(1.011)
SumLnEmpl	0.03	(0.025)	0.02	(0.025)	0.02	(0.025)	0.03	(0.025)
AbsDiffLnEmpl	0.19***	(0.031)	0.19***	(0.031)	0.19***	(0.031)	0.19***	(0.031)
σ^2 [b]	0.41	(0.103)	0.41	(0.104)	0.4	(0.104)	0.39	(0.103)
AIC	3084.83		3082.86		3084.59		3088.48	

[a] N=20910 firm-pair observations from crossing 205 firms; standard errors in brackets; *,**,*** signify 5%, 1% and 0.1% rejection levels of significance.

[b] The estimate of random effects variance follows a log-normal distribution and are therefore strictly positive.

separate estimation, model 3, and joint estimation, model 4. Introduction of technological variables decreases the coefficient of joint network centrality, *sumLnDeg*, by a magnitude of about two standard errors. The estimate of *prior ties* remains stable when estimated jointly with technological variables.

Interaction terms in models 5 to 8 are all insignificant except one. This suggests that social network effects do not moderate the technological-distance effect. In other words, social proximity does not trade off for technological proximity. The effect of technological distance on alliance formation remains unchanged by letting it interact with social network variables.

To summarize, both the social model and the technology model are informative for alliance formation. The social model fits the data better. Introduction of social and technology variables in the joint estimation improves the model fit. Furthermore, most coefficient estimates remain stable in the joint model compared to separate estimation, and there are no interaction effects between social network variables and the technological distance effect. Therefore, technological and social factors are capturing distinct and largely independent aspects of the alliance decision. The notable exception is that joint centrality in the network, *sumLnDeg*, and joint size of the patent portfolios, *sumLnPC*, seem to capture related aspects as both decrease when estimated jointly. The question of how to interpret this effect is discussed in the next section 4.4.2, based on further estimations.

Interpretation of Coefficients The effect of a marginal change of social and technological characteristics on the probability of alliance formation informs us about their relative importance. We have calculated marginal effects for significant social and technological variables in the joint model, 4. In the logit model, marginal effects differ over observations because they depend on the overall probability of success. In other words a marginal change of one characteristic is going to affect firm-dyads differently as soon as they differ in any of the characteristics taken into account by the model. Therefore, marginal effects as well as their significance for individual firm-pairs spread considerably over the population. Results on marginal effects for each firm-pair are provided in the appendix C.3. A good intuition however is gained by giving examples of marginal effects for 'typical' firms. This is done in the following, first for technological and then for social network effects.

A marginal increase in *overlap* increases the probability of alliance formation significantly for firm-pairs with an *overlap* between 0 and around 0.4. Further increase of *overlap* for firm-pairs with *overlap* between 0.4 to 0.7 still positively affects the probability of alliance formation but not significantly. The point of optimal technological distance is reached at around 0.7 *overlap*. From then on further increasing the *overlap* reduces the probability of alliance formation, where the change in probability is not significantly different from zero. The actual relevance of *overlap* for research alliance formation is clarified in an example.

Example 1 (Marginal Effect of overlap) *Consider a dyad, in which one firm covers* 10 *patent classes and the other firm covers* 15 *patent classes. This is a typical configuration, because* 10 *patent classes is the median in the firm population and* 15 *is the* 0.75 *quantile. Assume further that the firms have* 5 *patent classes in common. This yields an 'overlap' of* $5/20 = 0.25$*, close to the population average of* 0.3 *'overlap'. Five more patent classes in common, increases the 'overlap' to* $10/20 = 0.5$ *'overlap'. This is a* 100% *increase and corresponds to one standard deviation change (*0.25*). The marginal effect for firm-dyads having an 'overlap' of* 0.25 *on average is positive at* 0.025 *and significant. Thus, a one standard deviation increase implies on average an increase in probability of* $0.025 \cdot 100\% = 2.5\%$*. This is a considerable effect given the overall rate of success of* 2%*.*

The average marginal effects of the size difference of the firm-pair's patent portfolios, *absDiffLnPC*, increases with increasing size differences. Marginal effects are overall significant with a spread between 0 and 0.04. The following example suggests that the technology-distance effect is more important than the effect of differences in the patent portfolio.

Example 2 (Marginal Effect of absDiffLnPC) *Consider a dyad, in which one firm applied for* 1140 *patents and the other firm applied for* 50 *patents. Since the number of patent applications is very skewed, such cases are common. The log-transformed patent counts become approximately* $LnPC = 7$ *and* $LnPC = 4$ *yielding 'absDiffLnPC'* $= 3$*, close to the average of* 2.4*. A one standard deviation increase of* 1.75 *represents an increase of* 58%*. This is obtained for example by increasing the number of patents for the first firm to* 6300 *patents or decreasing the number of patents of the second firm to* 5 *patents. The average marginal effect for 'absDiffLnPC' of* 3 *is* 0.003*. Thus, a one standard deviation change implies an increase in probability of* 0.174% *(*$0.003 \cdot 58\%$*). This effect is one order of magnitude below the overall rate of success of* 2%*.*

Interpretation of social network effects is also meaningful in terms of marginal effects. Marginal effects of changes of *prior ties* are always positive and mostly significant (see appendix C.3). On average, firm-pairs with *prior ties* have a higher probability of 1.2% compared to firms having no prior tie.

For joint network centrality of a firm-pair, *sumLnDeg*, marginal effects are positive and significant for all firm-pair observations. The effect is relatively weak, as the example suggests.

Example 3 (Marginal Effect of sumLnDeg) *Focal firms on average have* 6 *alliances in the prior network. Because the median is lower (at* 2 *prior alliances), assume* *that there is a dyad where both firms have* 3 *alliances. This yield a joint centrality of 'sumLnDeg'* = 2.8*, which is close to the average of* 2.6*. An increase of one standard deviation (*1.7*) represents a* 60% *increase. This compares to an increase in the number of alliances of one firm by* 17 *alliances or an increase in the number of alliances of both firms by* 6 *alliances. The marginal effect for firm-pairs with 'sumLnDeg'* = 2.8 *in average is* 0.004*. Thus, a one standard deviation increase implies an increase in probability of* $0.004 \cdot 60\% = 0.24\%$.

Summary The estimates as well as marginal effects show that technological and social network effects are equally influential for alliance formation. When estimated separately both groups of factors fit the data similarly well (social network effects fit slightly better). In the joint estimation coefficients remain rather stable compared to separate estimation. In addition, there are no interaction effects between social factors and technological distance. Therefore, both groups of factors seem to capture distinct aspects of alliance formation.

Interpretation of the effects has been based on the joint estimation in model 4. We find that technological proximity (*overlap*) is valuable for distant firm-pairs (*overlap* between 0 and 0.4). For the average firm-pair with *overlap* 0.25 a one standard deviation increase in *overlap* increases the probability of alliance formation by 2.5%. This is a large effect, given the average probability of alliance formation of 2%. The effect of *prior ties* is similarly strong. Furthermore, we find a preference for differently sized patent portfolios, *absDiffLnPC*, and for high joint centrality in the prior network, *sumLnDeg*. Both effects are moderate. A one standard deviation increase of *absDiffLnPC* and *sumLnDeg* increases in average the probability of alliance formation by 0.174% and 0.24%, respectively.

Ego-Network Structures

Based on simulation of networks using the model estimates gained above, we derived the expected network position of each firm. The correlation of expected with observed network positions shows how well the respective model of dyad formation explains the higher-level phenomenon of a firm's ego-network structure. Broadly, the results show that model 2, including technological characteristics, and model 3, including social network characteristics, both improve significantly the base model 1 which includes only information on firm size. The social model 3 predicts the firms' ego-network structure better than does the technology model 2. Joint estimation of technological and social variables in model 4 outperforms separate estimation.

Table 4.6 gives the correlation coefficients for each model (columns) and network measure describing the firm network position (rows). We test the null hypothesis of zero correlation (indicated by *) as well as the null hypothesis that correlation coefficient's of two models are equal.[8]

Table 4.6: *Pearson's correlation of observed and expected firm-ego network statistics* [a]

		Model 1	Model 2	Model 3	Model 4
Degree	r_m [b]	0.49***	0.64***	0.71***	0.73***
	$P_{m=model\,1}$ [c]	–	0.000	0.000	0.000
	$P_{m=model\,2}$	–	–	0.013	0.061
	$P_{m=model\,3}$	–	–	–	0.000
Closeness	r_m	0.13	0.33***	0.42***	0.43***
	$P_{m=model\,1}$	–	0.004	0.000	0.000
	$P_{m=model\,2}$	–	–	0.075	0.009
	$P_{m=model\,3}$	–	–	–	0.252
Clustering	r_m	-0.09	-0.02	0.02	0.05
	$P_{m=model\,1}$	–	0.235	0.120	0.068
	$P_{m=model\,2}$	–	–	0.237	0.098
	$P_{m=model\,3}$	–	–	–	0.233
Triangles	r_m	0.19**	0.32***	0.38***	0.40***
	$P_{m=model\,1}$	–	0.023	0.003	0.002
	$P_{m=model\,2}$	–	–	0.124	0.049
	$P_{m=model\,3}$	–	–	–	0.070

[a] Expectations are based on estimates of the random firm effects model by simple monte carlo estimation with 1000 draws.

[b] r_m denotes the correlation coefficient. *,**,*** signify 5%, 1% and 0.1% rejection levels of the null hypothesis that correlation coefficient is zero.

[c] $P_{m=model\,x}$ is rejection level of the null hypothesis that correlation coefficients of models m and x are equal (one-sided tests).

Base model 1 includes only firm size controls. Expected and observed degree and triangles over firms are significantly correlated and, hence, base model 1 has some predictive power with respect to these network measures. The technology model, 2, adds information on the firm's technological position and thereby improves significantly predictions of the base model 1 in terms of degree, triangles and especially closeness (see table 4.6, column 'model 2' and rows $P_{m=model\,1}$ for each network measure). Similarly, model 3 adds information on social embeddedness to the size information in

[8] Tests for the null hypothesis that correlation coefficients for two models are equal are based on Williamson's test statistic for dependent correlation coefficients as described in (Steiger, 1980, p.246); all tests are one-sided.

model 1, which yields even higher correlations compared to the technology model 2. In particular, the social model 3 predicts degree and closeness significantly better than does the technology model 2 (column 'model 3', rows $P_{m=model\,2}$). Finally model 4 (joint estimation of social and technological position) improves models 2 and 3 significantly with respect to degree and triangles. Correlations of closeness and clustering is significantly higher than for the technology model 2 but not when compared to model 3 (see column 'model 4', rows $P_{m=model\,2}$ and $P_{m=model\,3}$). Finally, note that no model is capable of predicting the firms' clustering coefficient. Probably due to the low number of triangles in the network and the normalization by degree it is very difficult to predict.

Steady increase of correlation coefficients from model 1 to model 4 implies an ordering of the models with respect to their predictive power of ego-network structures. The ordering is the same as implied by the Akaike Information Criterion (AIC) of model fit when estimating alliance formation of firm-pairs. Thus, the added value of firm-level predictions is not the finding that one model fits better the dyad level and another the firm level. The real value is simply to recognize what model fit on the dyad level actually implies on the firm level. The important finding is that the firm's ego-network structure can be predicted to a large extent simply by the relationship of firm-pairs in technological and social space.

Global Network Structures

Figure 4.1 compares expected with observed network measure distributions. The figure provides the Kullback Leibler Information Criterion (KLIC) to assess how close expected and observed distributions are.[9] Visual inspection of expected network measure distributions and their 90% confidence intervals, however, is more informative.

The ordering of models with respect to how expected distributions fit observed distributions is the same as model fit on the dyad and firm level. However, significant differences in how the models fit observed network measure distributions are observed only for the distribution of closeness centrality. All models predict very well the degree distribution and perform badly with respect to triangles and clustering distributions.

The degree distribution is shown in figure 4.1 upper left panel. It is difficult to recognize any difference between the models visually. Because all models predict the degree distribution equally well, firm size information seems to be sufficient to infer on the degree distribution of the network.

[9] The KLIC for discrete distributions equals $KLIC(p, \pi) = \sum p(y) \ln(p(y)/\pi(y))$ and measures how close the distribution $p(y)$ is to a reference distribution $\pi(y)$. $KLIC(p, \pi)$ is strictly convex, $KLIC(p, \pi) > 0$ always and $KLIC(p, \pi) = 0 \iff p = \pi$. We calculate the KLIC for discrete distributions because our reference distribution, the observed network measure distribution, is discrete. This makes necessary to discretize the expected network measure distributions. The discretization is presented together with the results.

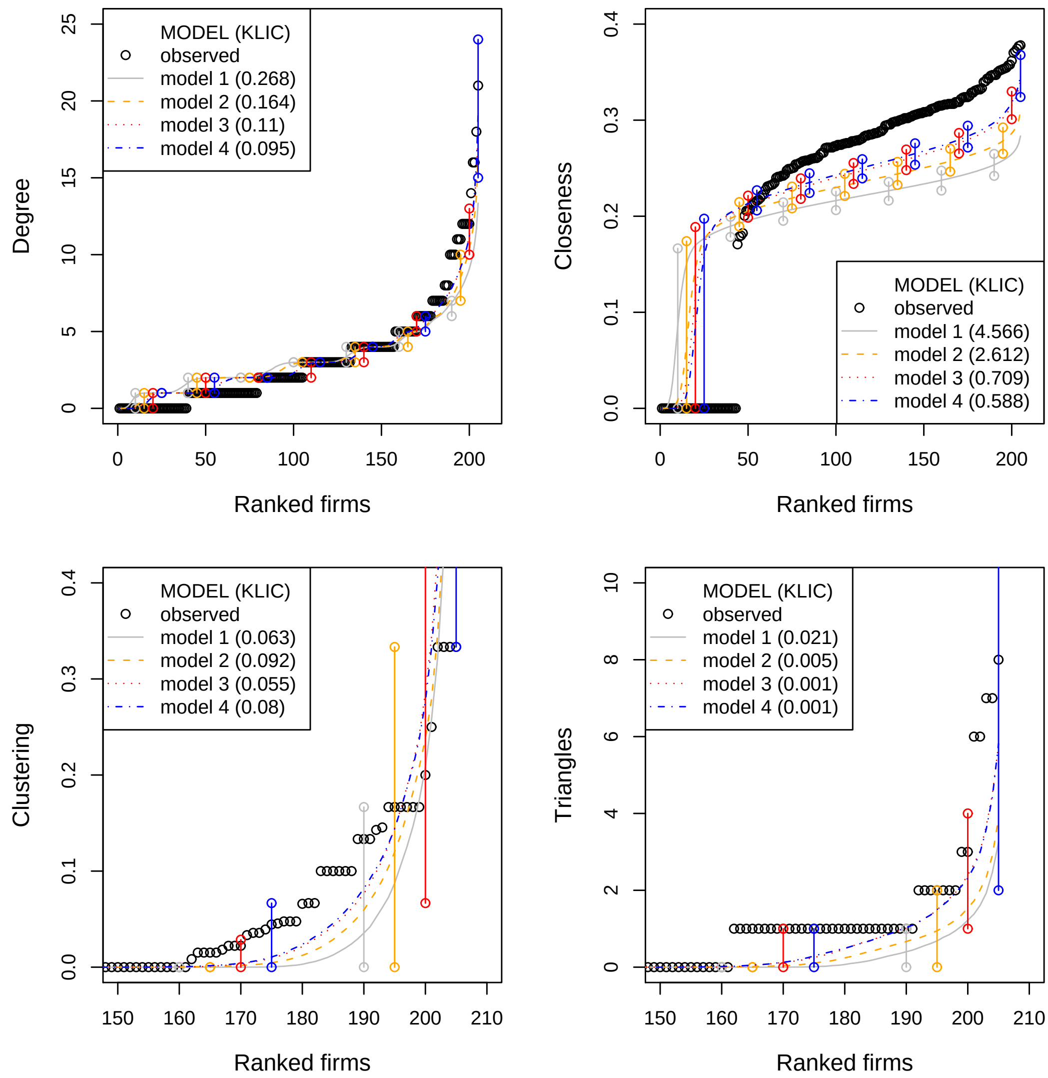

Figure 4.1: *Observed and expected network measure distributions. Black circles are observations, lines give the average over 1000 simulations, circles connected by vertical lines indicate 90%-confidence intervals. KLIC compares probability masses according to the following cutpoints: degree (1, 2, 3, 5), closeness (0, 0.258, 0.287, 0.317), clustering (0, 0.015, 0.041, 0.1, 0.167), triangles (1, 2).*

Expected distributions of closeness centrality differ across models (see the upper right panel of figure 4.1). All models expect a less skewed closeness distribution which is on a lower level than the observed distribution. The technology model 2 implies a more skewed distribution which is on a higher level than that of the base model 1. The social network model 3 comes even closer to the observed distribution. Further improvement due to joint estimation of technological and social factors in model 4 is marginal. The closeness distribution of the observed network is on a high level and skewed due to its core-periphery structure. Thus, the size model yields a random network with sufficient hubs to meet the degree distribution, but it does not imply the observed core-periphery structure. In this respect, technological and social network variables clearly improve expectations.

Distributions of clustering and triangles are given in the lower left and right panel respectively. Because only 40 firms are involved in triangles only the upper tails of the distributions are displayed (150th to 205th firm). Both tails seem to be similarly difficult to predict: expected distributions are below observed distributions and not significantly different from each other; their 90% confidence largely overlap. Within these uncertainties, we observe the same order of models with respect to their predictive power as throughout the analysis: firm size model 1, technology model 2, social network model 3 and, finally, technology and social network model 4.

4.4.2 Sensitivity Analysis

In the previous sections, we presented the estimation results of models including technological variables and social network variables. But what do these variables capture really? For interpretation of the results two issues seem to be especially relevant: Firstly, our indicator of technological fit seems to be rough. Secondly, the social network variables are similar to lagged variables as they are measured on the prior network of alliances. The consequence of both issues together is that our estimates represent a lower bound for technological effects and an upper bound for social network effects. Particularly, we can not exclude the possibility that social network variables are purely indirect indicators of technological effects. Because this has serious implications on our work, we elaborate this argument in the following.

The indicator of technological fit, overlap, is rough. The firm's technological capability is described by its coverage of patent classes on the 4-digit level. This information does not contain many aspects on the firm's technology which influence the decision to form an alliance. In particular, with our measurement differences within the patent classes disappear (as do similarities across patent classes). In the best case, this inaccuracy imposes a considerable measurement error on our measure of technological fit.

The social network variables are measured on the prior network of alliances. The principle argument is that the prior network of alliances proxies the social network among the firms. However, a network is the aggregate of alliance decisions and, hence, reflects all factors which influence alliance decisions. Those factors which remain stable over time are going to be reflected in the prior network as well as in the current network. Because social network variables represent structural characteristics of the prior network, they also incorporate such stable factors. More specifically, social network variables represent specific network configurations and therefore incorporate the effect of all stable, systematic factors on respective network configurations.

A simple thought experiment illustrates that within our estimation approach any significant social network variable is susceptible of spurious path dependency due to measurement error or omitted variables. Imagine that two networks are deterministically determined by several exogenous factors. Some factors change randomly from the first to the second network and some remain constant. Now, measure social network variables on the first network and estimate their coefficients on the second network jointly with the constant determining factors. If all constant factors are included, social network measures do not add information and remain insignificant. But the more constant factors are excluded from the regression or become contaminated with measurement errors, the more the social network measures add to the regression because they incorporate the information which has been lost. In this sense social network measures indicate structural stability, be it given socially, economically, technologically or in any other way.

Because measurement errors have in principle the same effect as omitted variables, our estimates of social network factors are not fully controlled for technological or economic factors. Therefore, it is likely that we overestimate their effect and give an upper bound. Similarly, the effect of technological fit is likely to be underestimated due to measurement error, yielding a lower bound. Particularly, if firms' technological capabilities (i.e. coverage of patent classes) change slowly.

Since we estimate the formation of research alliances, social network variables measured on the prior research network are more likely to introduce spurious path dependency than those measured on the prior network of non-research alliances. In addition, social variables from the prior research network are most likely to capture stable technological factors. Therefore, network measures based on the research network are most likely to be affected when we control for technological factors using our technological variables. We test this idea with two alternative estimations of model 3, which includes only social network variables and model 4, which includes technological and social variables. Estimations differ because we now split social network variables into the contribution coming from past research alliances and the contribution coming from past non-research alliances. Our reasoning is supported if social network variables of the prior research network become weaker by introduction of technological variables. In order to remain parsimonious, we split only those variables which have been significant in table 4.4, i.e. *prior ties* and joint network centrality (*sumLnDeg*).

Estimation results are given in the table 4.7. Model 3' estimates only social network variables, model 4' controls for technological characteristics. The estimate of joint centrality in the research network (*research sumLnDeg*) decreases considerably and becomes insignificant by the introduction of technological variables in model 4'. This means that *research sumLnDeg* represents neither status homophily nor accumulated advantage but in fact catches structural stability of the network due to stability of the firm's position in technological space. Of course, this concern carries over to the interpretation of *non-research sumLnDeg*, which might capture structural stability due to other, especially economic factors.

Table 4.7: *Random effects logit models of alliance formation (jointtech), research and non-research network* [a]

	Model 3'	Model 4'
Intercept	-7.03*** (0.355)	-7.74*** (0.419)
Overlap	–	3.22** (1.042)
Overlap^2	–	-2.49* (1.104)
SumLnPC	–	0.04 (0.034)
AbsDiffLnPC	–	0.15*** (0.044)
Research prior ties	0.67** (0.275)	0.72** (0.279)
Non-research prior ties	0.65** (0.214)	0.63** (0.216)
Common partners	-0.03 (0.081)	0 (0.084)
Research sumLnDeg	0.21** (0.069)	0.12 (0.073)
Non-research sumLnDeg	0.34*** (0.067)	0.31*** (0.067)
AbsDiffLnDeg	0.03 (0.056)	0 (0.058)
AbsDiffLnEmpl	0.2*** (0.027)	0.18*** (0.031)
SumLnEmpl	0.05* (0.022)	0.02 (0.025)
σ^2 [b]	0.43 (0.103)	0.42 (0.104)
AIC	3107.03	3086

[a] N=20910 firm-pair observations from crossing 205 firms; standard errors in brackets; *,**,*** signify 5%, 1% and 0.1% rejection levels of significance.

[b] The estimate of random effects variance follows a log-normal distribution and are therefore strictly positive.

On the other hand, introduction of technological effects in model 4' does not decrease the coefficient estimate of prior research ties. Thus, the alternative estimation does not support the idea that *prior research ties* is in fact just capturing technological stability. Therefore, one might conclude that prior ties has in itself an effect which is coherent with theoretical arguments of organizational learning and structural sociology. However, an alternative explanation of the estimation results also might be correct. Because technological fit of two firms in the real-world is far more complex than our technological variables are able to capture, prior ties might be simply the best proxy of technological fit that we have.

Another issue is that, up to now, we have assumed that there are no measurement errors of social network variables. We know that this is not the case. Therefore, the upper bound of social network variables postulated above is not strict. The bound might increase as measurement of social network variables improves. In particular, our sample includes 68 firms with no registered prior alliance and it is likely that many of them in reality did have (an) alliance(s) (see section 4.3.1). In order to see how these firms affected our results, we ran additional regressions excluding these firms from the sample. This restriction does not induce major changes in the social network coefficient estimates (table 4.4).

4.5 Discussion and Conclusion

Coleman's theory of structural sociology describes economic behavior as purposeful action enabled and constrained by social structure (Coleman, 1986). The literature on the formation of research alliances up to now emphasized the purpose by focusing on technological factors. Research on alliance formation in general emphasized opportunities and constraints imposed by social structure. This chapter proposes that firms' embeddedness in both technological space and in social space is influential in the formation of pairwise research alliances which, in turn, has implications on the firm's ego-network structure and the global network structure.

Our estimation results support this view. Technological distance between two firms and their prior alliance history are both found to be important for joint research alliances. Still relevant but less important are differences in the size of the firms' patent portfolios and joint centrality in the prior alliance network. In addition, we found that the estimated firm-pair decision model which takes into account both technological and social factors, predicts firm ego-networks better than only taking into account either technological or social factors. Thus, the two types of factors complement each other. With respect to distributions of network statistics, the value of adding social network factors to technological factors is limited to the closeness distribution. Whereas the degree distribution is met very well by all models, the fit to triangles and clustering distributions might be improved in the future.

The insight that econometric models of pairwise alliance formation do not necessarily generate networks which cohere with higher-level network structures is already valuable in itself. In principle, it is desirable to have models at hand which produce a coherent picture of all relevant aspects of reality. Structural theories argue that the firms' ego-networks and the global network structure are relevant aspects of reality. Most empirical work in the literature on alliance formation takes this into account only by introducing social network variables as regressors. Implications of (estimated) alliance formation models on higher-level network structures are usually not considered in this literature. Comparison of expected and observed network measure distributions of models of network formation has been suggested recently by Goodreau et al. (2007). We extend this approach and consider in addition ego-network structures. Our analysis shows that this is valuable because alliance formation models do not necessarily cohere with higher-level network structures. One possible approach to reach this goal in future research is to introduce sufficient statistics on network statistics in the model, as suggested for example by Snijders et al. (2006).[10]

Our sensitivity analysis points to an even more pressing issue. We show that some social network variables may incorporate spurious path dependency. This means that social network variables capture not only the effect of the network but also incorporate effects of stable, exogenous factors. The implication is that our estimates represent upper bounds of 'true' network effects. It is important to note that this issue concerns not only our analysis but the majority of empirical studies on the effect of prior alliance networks on alliance activity. This includes highly-cited studies which investigate the effect of the firms' embeddedness in the alliance network on pairwise alliance formation by Gulati and Gargiulo (1999), on partner choice by Powell et al. (2005) or on rates of alliance formation by Ahuja (2000). Therefore, controlling for stable structures is an important issue for future research.

[10] We tried this approach but failed to reach convergence in the estimation which is still an issue to be resolved (Goodreau et al., 2007).

APPENDIX C

Statistics and Analysis

C.1 Network Description

Table C.1 presents network statistics for various networks depending on the time span it has been formed, the population it includes, and the type of alliance in the network. The analysis focuses on effects of the prior global pharmaceutical network (first row in table C.1) on the current research network among sampled firms (last row in table C.1).

The prior global network and the (current) global network both formed during a six year period. Yet, the current network is three times as large as the prior network. The growth is due to the entry of new firms in the network. The average number of alliances (*degree*) per firm slightly decreased from 3.2 alliances in the prior period (1995-2000) to 2.9 alliances in the current period (2001-2006). During growth the network became more centralized in terms of degree, which can be explained with the tendency of new entrants to connect with firms in the core.[1]

C.2 Hausman Test

In the fixed effects model firm dummies control for the rate of alliance formation of the firm. If for a firm no alliance is observed, the dummy coefficient takes on minus infinity and hence is not defined. Therefore, a comparison of fixed and random effects can only be done on a restricted set of 166 firms, which includes only firms with at

[1] Higher centralization is indicated by increasing right skewness of the degree distribution from 4 in the prior global network to 10 in the current global network

Table C.1: *Network statistics*

Time span		1995-2000	1995-2000	1995-2000	1995-2000	2001-2006	2001-2006	2001-2006	2001-2006
Alliance type		Any alliance	Any alliance	Jointtech	Jointtech	Any alliance	Any alliance	Jointtech	Jointtech
Firm population		All firms	Focal firms	All firms	Focal firms	All firms	Focal firms	All firms	Focal firms
Vertices		1403.00	205.00	1403.00	205.00	5094.00	205.00	5092.00	205.00
Edges		2256.00	213.00	954.00	99.00	7240.00	690.00	3525.00	339.00
Main component [a]		1193.00	102.00	590.00	73.00	4053.00	194.00	2196.00	162.00
	Mean	3.22	2.08	1.36	0.97	2.84	6.73	1.38	3.31
Degree	Var.	28.62	10.07	6.34	2.80	35.12	38.91	12.62	12.91
	Skew.	4.50	2.29	4.03	2.21	10.39	2.19	11.97	1.98
	Mean	0.20	0.16	0.09	0.09	0.16	0.33	0.08	0.23
Closeness	Var.	0.01	0.03	0.01	0.01	0.01	0.01	0.01	0.01
	Skew.	-1.45	0.16	0.45	0.75	-1.07	-2.41	0.41	-1.08
	Mean	0.02	0.05	0.01	0.02	0.01	0.09	0.00	0.02
Clustering	Var.	0.01	0.02	0.00	0.01	0.00	0.01	0.00	0.00
	Skew.	7.81	4.81	14.38	8.53	13.29	1.96	27.78	3.35
	Mean	0.42	0.41	0.06	0.06	0.28	3.21	0.04	0.41
Triangles	Var.	3.10	1.30	0.12	0.06	4.44	28.22	0.15	1.34
	Skew.	7.26	4.11	8.13	4.65	14.04	2.66	16.52	4.47

[a] indicates the number of vertices in the largest connected subgraph.

least one alliance partner in the network. For econometric details please see chapter 3, Appendix B.1.

Table C.2 gives the results of the random and fixed effects specification as well as the Hausman test for model 4. For no coefficient the null hypothesis that random and fixed effects coefficients are equal can be rejected. This justifies to base the analysis in the main text on random effects estimates.

Table C.2: *Hausman's test (model 4)* [a]

	Random effects		Fixed effects		H-value	$Pr(>\|H\|)$
Intercept	-6.99***	(0.442)	–		–	–
Overlap	2.59**	(1.056)	1.96	(1.829)	0.18	0.67
Overlap^2	-1.57	(1.114)	-1.53	(1.738)	0.00	0.98
SumLnPC	0.00	(0.034)	-0.32	(1.405)	0.05	0.82
AbsDiffLnPC	0.2***	(0.045)	0.15**	(0.062)	1.41	0.24
Prior ties	0.76***	(0.162)	0.81***	(0.168)	1.13	0.29
Common partners	0.06	(0.084)	-0.02	(0.104)	1.77	0.18
SumLnDeg	0.27***	(0.05)	1.02	(2.009)	0.14	0.71
AbsDiffLnDeg	0.06	(0.06)	0.00	(0.074)	1.73	0.19
AbsDiffLnEmpl	0.19***	(0.032)	0.16***	(0.038)	0.16	0.69
SumLnEmpl	0.01	(0.025)	-0.40	(1.03)	1.78	0.18
σ^2	0.50	(0.113)	–		–	–
AIC	2894.64		2990.05		–	–

[a] N=13695 firm-pair observations from crossing 166 firms. Standard errors in brackets; *,**,*** signify 5%, 1% and 0.1% rejection levels of significance.

[b] Firm dummy estimates not displayed.

[c] $Pr(>|H|)$ is significance level of rejection of equality of coefficients from chi-square distributed H-value with 1 d.o.f.

C.3 Marginal Effects

The dependent variables are interpreted by their marginal effect on the dyadic alliance decision. Marginal effects are defined to be the first derivative of the probability of success with respect to the variable. Because the logit model is non-linear, each observation has its own marginal effects which is a function of the estimated coefficients and the independent variables of the observation. Their distribution has been calculated using the delta-method (Cameron and Trivedi, 2005, p.227ff.).

Figures C.1 and C.2 display marginal effects of technological and social variables, respectively. Estimation is based on the model 4, which includes both types of variables.

The discussion of marginal effects is in the results section 4.4.

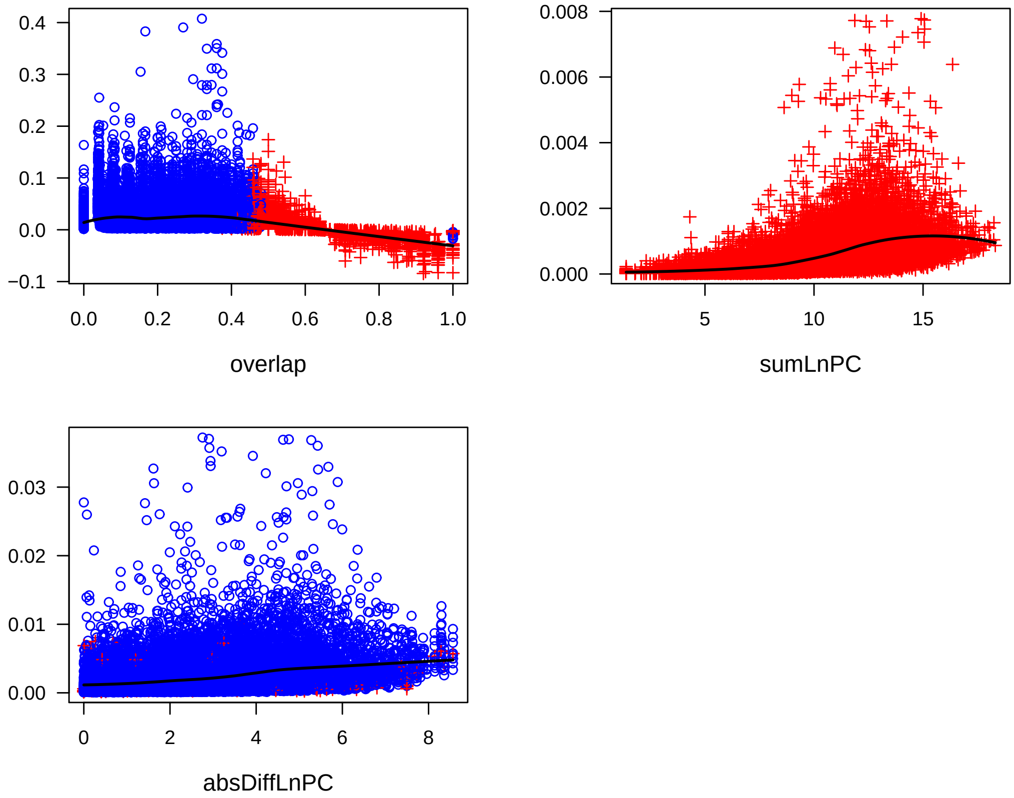

Figure C.1: *Marginal effects of technology factors as estimated in model 4, where sumLnPC and absDiffLnPC denote the sum and absolute difference of log-transformed patent counts respectively. Blue circles (red crosses) indicate (non-)significance on 5%-level of a two-tailed z-test. Lines give a local average.*

C.4 Sensitivity Analysis - Restricted Sample

The sample which we use for the analysis in the main text contains 68 firms for which no prior alliance between the years 1995 and 2000 is registered in the data base. Out of these 68 firms, we chose randomly 10 firms and found that 8 of these in fact did have an alliance. Estimations including firms which are falsely coded as not having a prior alliance might yield a downward-bias of social network estimates. Therefore, we present in table C.3 estimations of a restricted estimation set, which includes only firms with prior alliances. The result shows that social network coefficients have not been

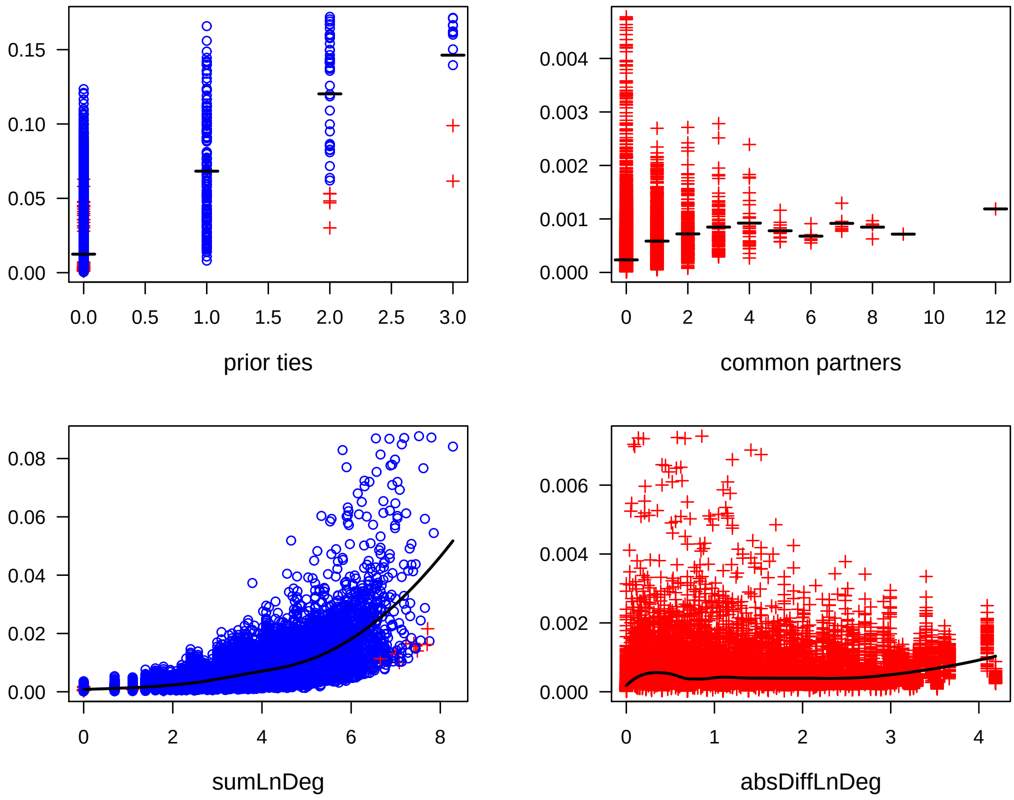

Figure C.2: *Marginal effects of social factors as estimated in model 4, where sumLnDeg and absDiffLnDeg denote the sum and absolute difference of log-transformed degree respectively. Blue circles (red crosses) indicate (non-)significance on 5%-level of a two-tailed z-test. Lines give a local average.*

negatively effected by inclusion of firms without prior alliances. However, technological coefficients changed slightly and became less significant as compared to the estimation on the full working set.

Table C.3: *Random effects logit models of alliance formation (jointtech), restricted sample* [a]

	Model 4'		Model 5'	
Intercept	-6.8***	(0.505)	-7.32***	(0.583)
Overlap	–		2.29*	(1.329)
Overlap^2	–		-1.66	(1.354)
SumLnPC	–		0.04	(0.04)
AbsDiffLnPC	–		0.15**	(0.053)
Prior ties	0.7***	(0.159)	0.7***	(0.157)
Common partners	0.03	(0.082)	0.05	(0.085)
SumLnDeg	0.44***	(0.069)	0.35***	(0.078)
AbsDiffLnDeg	0.03	(0.086)	-0.01	(0.088)
AbsDiffLnEmpl	0.23***	(0.033)	0.2***	(0.038)
SumLnEmpl	0.02	(0.028)	0	(0.031)
σ^2 [b]	0.39	(0.128)	0.36	(0.13)
AIC	2055.38		2048.35	

[a] N=9316 firm-pair observations from crossing 137 firms; standard errors in brackets; *,**,*** signify 5%, 1% and 0.1% rejection levels of significance.

[b] The estimate of random effects variance follows a log-normal distribution and are therefore strictly positive.

CHAPTER 5

Modularity in the Vaccine Industry

5.1 Introduction

The pharmaceutical industry is characterized by an extensive division of innovative labor among firms and other institutions (Malerba, 2005). Organizations with heterogeneous capabilities engage in interrelated innovation activities along the pharmaceutical value chain. The division of innovative labor is necessarily accompanied by inter-organizational interaction. How innovation activities are mapped to organizations and how organizations interact is crucial for the overall functioning of the innovation system (Marengo and Dosi, 2005) as well as the prospects of the organizations (Jacobides et al., 2006).

This chapter investigates the division of innovative labor among firms in the vaccine industry. The specificity of this pharmaceutical sub-sector arises from the product architecture of vaccines. The effectiveness of a vaccine rests on three functions. Research on the three functional elements draws from specific scientific domains and is handled increasingly independently from each other. This problem decomposition is visible in an organizational division of research. New biotechnology firms specialize in specific vaccine components and do research in parallel, largely independently of each other. At a later stage, their research results are integrated for the development of novel vaccines. Typically, such a work flow is associated with modular design in engineering. However, the coordination principle is different. Complex product development usually invokes the design of a product architecture, i.e. the mapping of functions to components and specification of their interfaces. Contrary to complex products, the product architecture of vaccines is provided by the scientific landscape. Thus, the vaccine industry exemplifies how the scientific landscape allows for and coordinates organizational division of pharmaceutical research.

The analysis in this chapter continues work which started with the research project ‘MIDeV’ (“Modularite et Incitations dans le Developpement de Vaccins geniques”). Eventually, this project led to a publication on modular innovation of new vaccines with a focus on the dual role of patents as exclusion and coordination device (Bureth et al., 2007). The article argues that, on the one hand, firms use patents to exclude competitors with similar technological specialization from their research. On the other hand, patents signal technological competence and certify property rights which enables technology transfers between firms with complementary technologies. In that work collaboration between different technological domains was measured by simple frequency counts which suggest that alliance formation is more frequent across technological domains than within technological domains. The approach is unsatisfactory because frequency counts do not take into account the number of firms in each technological class or that firms have multiple specializations.

The analysis in this chapter deviates in three major points from the previous analysis of Bureth et al. (2007). Firstly, the population considered in the analysis is extended. Besides biotechnology firms specialized in vaccine components the analysis now includes also general purpose technology firms and integrated pharmaceutical firms. Secondly, the direction of technology flow between these types of firms is considered. Thirdly, hypotheses on the pattern of technology flow are developed and tested using exact tests.

The chapter is structured as follows. The next section provides the background for the analysis. It includes an overview on the market for vaccines as well as the technological characteristics of vaccines, followed by a discussion on modularity of vaccines and how this affects the division of work in the industry. The empirical analysis, section 5.3, presents the sample, the estimation strategy and the results of the analysis. Section 5.4 further investigates technology sourcing and supply of two individual firms. The two cases help to better understand the analysis results. The final section concludes.

5.2 Vaccines and Modularity

5.2.1 Market

Today, there are vaccines against 26 infectious diseases on the market. Together they generate an annual turnover of ca. 9 billion Euros. This is approximately 1.5% of the worldwide turnover of 550 billion Euros stemming from pharmaceuticals. The market for vaccines is highly concentrated. It is clearly dominated by the five firms Merck, GlaxoSmithKline, sanofi-aventis, Wyeth and Novartis, where the first three players take a market share of 85%. For no indication are there more than two firms offering a vaccine.[1]

The market structure is the result of a concentration process starting 50 years ago. It has been argued that actors withdrew from the vaccine market because margins are low relative to other pharmaceutical investments (Pauly, 2005). The costs however are as high as for other medicaments (500 800 million $), as are the development times (15 to 20 years) and the increasing burden through the clinical stages with high bureaucratic costs for approval (Grabowski et al., 2004; Plotkin, 2005). Especially for vaccines, it might be difficult to recoup such high fixed costs because a successful vaccine will automatically reduce demand (Danzon and Pereira, 2005). The low competition per indication might be explained by the difficulty of product differentiation, since the more efficient vaccine is likely to take over the whole market (Danzon and Pereira, 2005).

Nevertheless some new players increased their US market share from 3% in 1999 to 20% in 2002 through differentiation, new indications or improved versions. For example, they entered the market with transitory vaccines for travelling, a new vaccine against cholesterol (Avant Immunotherapeutics), variation of administration (MedImmune) or improvement of parts of an existing vaccine (Corixa, Coley Pharmaceutical Group, CSL Limited) (Savopoulos, 2004).

The vaccine market is estimated to grow 20% annually in the next years, which approximates the growth prospects of the whole pharmaceutical market (30%) (Bonah et al., 2007). This translates into an estimated turnover of 18.4 billion Euros in 2010, of which 2/3 will be generated by new vaccines. Expectations for the long run are very high, because of the opportunities opened up by the biotechnological revolution. Besides more efficient development and improvement of vaccines for traditional indications, the vaccination principle is extended to further indications. Traditionally vaccines are prophylactic (prior infection) and target viruses which cause acute infections. Now, therapeutic vaccines (after infection) seem to be within reach. New indications are chronic infections caused by viruses like HIV, hepatitis C virus or human papillomavirus causing cancer (Berzofsky et al., 2004; Rogan and Babiuk, 2005). The new markets are expected to be highly profitable and firms increasingly invest to capture them (Pasternak et al., 2006).

The development of the vaccine sector represents one instance of the effect of the biotechnological revolution on the pharmaceutical industry (general insights are provided for example by Henderson et al., 1999; Galambos and Sturchio, 1998). Due to long development times, the vaccines offered do not reflect this revolution yet. However, the new opportunities opened up by scientific progress can be seen very clearly in the changed industry structure. In order to understand the change, some basic knowledge about the vaccine technology is appropriate:

[1] All market information from (Bonah et al., 2007, p.79-153).

5.2.2 Technological System

Traditionally, a vaccine is a preparation based on a pathogenic agent (bacteria, virus, parasite), which stimulates the production of antibodies or T cells without provoking the illness itself. New approaches often use the fact that the immune response is caused by the introduction of any antigen (a macromolecule provoking an immune response) having the same epitopes (characteristic part to which an antibody connects) as the pathogenic agent.[2] It is helpful to distinguish vaccines into those which replicate themselves in the organism of the patient, i.e. replicating vaccines, and those which do not, i.e. non-replicating or inactivated vaccines. There is a trade-off between the two: replicating vaccines cause an effective and long-lasting immune reaction, including a humoral response (production of antibodies) and a cell-mediated response (including among others T-cells, macrophages and killer cells). Inactive vaccines are less efficient, because they do not cause a cell-mediated response (e.g. T-cells) but only a humoral response (antibodies). In order to increase the immunological response, some compound (called an adjuvant) has to be added. On the other hand inactive vaccines are less risky. Since they are non-replicating, they are not infectious.

Traditionally an attenuated vaccine has been created by selection of non-virulent mutants. They became non-virulent either by spontaneous mutagenesis or mutations having been created by undirected processes with chemicals or heat. Inactivated vaccines used the whole killed pathogenic agent or, in case of a subunit vaccine, purified the subunit antigen in a costly process to remove toxic and immunosuppressive units of the agent.

Scientific advances have changed the development and the production of vaccines. Genetic engineering techniques allow for new ways of developing attenuated vaccines: Genes associated with the virulence can be identified and deleted or inactivated in order to make the agent inoffensive (gene-deleted attenuated vaccines). Another way is to choose an inoffensive virus or bacteria (the vector) and to transfect the antigen DNA. This virus then serves as a live vector which expresses the antigen (recombinant live vector vaccines). Furthermore, the production of subunit vaccines is altered by biology and genetic engineering tools. They allow for tailoring single proteins and for producing them in a cell system. Genomic and proteomic bioinformatics made possible rapid identification of protective epitopes (the counterpart of the antibody).

Yet a completely new possibility for vaccination is represented by DNA vaccines. The DNA which encodes the antigen is inserted into the cells of the patient, which then themselves act as producers of the vaccine. In principle the DNA might be delivered into the cell by microparticles or electroporation.

Problem decomposition is often mentioned as a consequence of the new scientific approaches in biopharmaceutical research (e.g. Henderson and Cockburn, 1994). The

[2]About technological developments in vaccines, see for example (Berzofsky et al., 2004; Rogan and Babiuk, 2005).

description of the new approaches for attenuated, inactivated or DNA vaccines shows how problem decomposition became concrete for vaccines. The three main functional elements of a vaccine are handled increasingly independently from each other (Bureth et al., 2007; Bonah et al., 2007). First, screening technologies and genetic mapping are used to identify the epitopes on the antigen, which characterize the virus and thus function as the target of the immune system (Antigen). Second, recombination techniques are able to combine this target with an appropriate vector, which is used as a carrier for delivery into the organism (Vector). Third, the immune response has to be stimulated. Most often this is done by adjuvants but also by appropriate choice and design of the vector (Adjuvant). Thus, the three major functions are now mainly represented by the complementary entities 1) Antigen, 2) Vector, and 3) Adjuvant.

From the property of problem decomposition, it follows that research becomes more specific. Since most new biotechnology firms have their origins in basic research, they are highly specialized and problem decomposition translates in an isomorphism between the scientific field and the industrial organization. Here isomorphism means that the boundaries of scientific topics and the technological boundaries of the firms have a high overlap rate and that the dependence structure among the scientific topics translates into a similar (technological) dependence structure among the firms. Bureth et al. (2007) show that the isomorphism concept is valid for the vaccine sector which means that firms specialized in 1) Antigen, 2) Vector, and 3) Adjuvant entered the industry. Thus, in the vaccine industry, we observe a division of innovative labor among firms which are specialized in vaccine components. In the literature on engineering design such a division of labor is usually considered to be facilitated by a modular product architecture. The following section discusses the extent to which vaccines actually are modular and how modularity affects the product development process.

5.2.3 Modularity in Product Development

The shift from the traditional to the new concept of a vaccine represents a shift from an integral to a nearly modular product architecture. Ulrich (1995, p.422) synthesizes different research streams on modularity and product design in order to provide a typology of product architectures. According to Ulrich (1995, p.422) a modular architecture is given when there is i) a one-to-one mapping of functions to components and when ii) the components are not coupled (de-coupled). "Two components are coupled if a change made to one component requires a change to the other component in order for the overall product to work correctly."(Ulrich, 1995, p.423) In contrast, an integral architecture maps several functions onto one component or splits functions over components which are not de-coupled (for definition see Ulrich, 1995, p.422).

A traditional vaccine consists of whole (attenuated) viruses or parts thereof. Thus, in the case of traditional vaccines, one element (the virus) provides all the functions of a vaccine. It serves as a vector, provides the antigen and also causes the immune-response.[3] Therefore, traditional vaccines have an integrated architecture where one component provides all functions. In contrast, novel vaccines have a nearly modular architecture. The one-to-one mapping of functions to elements is largely given for vaccines. The new biotechnological methods led to a conception of vaccines where each function is represented by a separate component. For example the antigen is now considered to be the expression of a certain DNA fragment. The second definitional criterion of a modular architecture is that the components are de-coupled. Also this is given to some extent because components are substitutable. Exchanging the DNA fragment which codes the antigen and maintaining the same vector and adjuvant combination might yield a well-functioning vaccine. Because a pathogen has several specific characteristics, even the same indication might be targeted with such an alternative product. However, de-coupling of components is not complete because interactions between components are not fully understood. Whether a new combination is valuable needs to be tested. Therefore, one might say that vaccines have a nearly modular architecture.

The product architecture is important because it influences the product development and the division of work in the industry. The design of a product architecture specifies which components provide which functions and how the components are interrelated. Shifting from an integral architecture to a modular product architecture may improve product life cycle management and make the organization of product development more efficient.

Within a modular product architecture changing one component does not necessitate changes in other components. Therefore it is possible to develop new products by replacing components or recombining components and to use the same components in multiple products (Ulrich, 1995). Thus innovations are more easily introduced and synergies over product lines may be realized. In addition, the organization of the development process might become more efficient. Von Hippel (1990) describes the innovation process as a network of tasks. Given some output from another task, a task consists of solving a certain problem and yields some input for subsequent tasks. Thus, tasks need to be coordinated and transactions take place between the tasks. Von Hippel argues that the need for coordination increases with the problem-solving interdependence between the tasks. Similar to the coupling of components in the product architecture, problem-solving interdependence captures the responsiveness of two tasks in the product development process. More specifically, the degree of problem-solving interdependence between two tasks is "the probability that efforts to perform one of the tasks to specification will require related problem-solving of the other."(von Hippel, 1990, p.409). A modular product architecture allows a partitioning such that the boundaries of the tasks match with the boundaries of the modules. This reduces the effort for coordination as well as transaction costs because problem-solving

[3] A qualification is that adjuvants have been added in traditional vaccines as well.

activities are only loosely coupled as long as they comply with the specification of the architecture. Also from an information-processing point of view de-coupling of tasks is beneficial because decisions with respect to the task can be made without the need to consider manifold interdependencies with other tasks (Simon, cited by von Hippel, 1990, p.409).

A modular organization makes the innovation process not only more efficient but also reduces time to innovation. De-coupling of problem-solving tasks oriented on a modular product architecture implies that components can be developed simultaneously by different groups or other organizational entities (Sanchez and Mahoney, 1996; Ulrich, 1995; von Hippel, 1990). The modular product architecture becomes the main structuring element because it provides all the information which is necessary to perform a certain task (Sanchez and Mahoney, 1996).

The discussion shows that the product architecture affects the innovation process which has been described as a system of problem-solving activities. This has further consequences. In order to solve a problem one needs to have the relevant knowledge and by solving a problem one usually learns something. Therefore, the assignment of innovation tasks needs to take into account the knowledge of the actors, and is going to affect the knowledge of the actors. Drawing from the differentiation of architectural and component knowledge by Henderson and Clark (1990),[4] Sanchez and Mahoney (1996) argue that organizational modularity generates specialization effects. Firms or other organizational entities which are predominantly focusing on a certain component are going to learn about the component. Those firms or entities which predominantly integrate components foster their architectural competence by architectural learning (Sanchez and Mahoney, 1996, p.73).

The study of Brusoni et al. (2001) provides an important qualification for this argument by noting that organizations which are involved in the innovation process are usually not completely de-coupled but loosely coupled. The authors investigate the role of engine manufacturers in the aircraft engine industry. The engine manufacturers act as system integrators who need to integrate several technologies in their engines, among which are engine control systems which they receive from external suppliers. The authors analyze how engine manufacturers, as systems integrators, accommodate the changing technology of engine control systems. The important contribution of Brusoni et al. (2001) is the observation that systems integrators need architectural knowledge as well as component knowledge.

> By knowing more, multitechnology firms can coordinate loosely coupled networks of suppliers of equipment, components, and specialized knowledge and maintain a capability for systems integration.(Brusoni et al., 2001, p.597)

[4] Roughly spoken, architectural knowledge is knowledge about the interrelationships of components, whereas component knowledge is about the inner functioning of the component.

The reason that a system integrator needs to maintain component knowledge is because organizations involved in the innovation process are not completely de-coupled but loosely coupled. Here, loose coupling means that organizational entities are separated (distinctiveness) but need to be coordinated (responsiveness) (Brusoni et al., 2001, p.610). Coordination between organizations is needed if the architecture is not completely modular. This is the case for example when (some) interdependencies between the components are not fully understood. Then, problem-solving tasks become interdependent and need to be adjusted by active coordination. However, active coordination may also be necessary because technologies are evolving over time. If progress of the technologies which underlie the different components is uneven, then adjustments of the product architecture might be necessary due to cascading effects across components (Brusoni et al., 2001, p.608). In the case when specialized knowledge producers are loosely coupled, Brusoni et al. (2001, p.608) ascribe a very active role to the system integrator. In the narrative account of the study, system integrators specify the functioning of the component as well as their relations at the beginning of the development process and actively adapt the architecture during the development process. In addition, technological advance in the technologies of individual components may trigger an architectural innovation by the systems integrator.

However, we may note that the importance of a systems integrator decreases, the more the organizations involved in product development are de-coupled. As an extreme example, consider a modular product with completely standardized components such as the mouse connecting to a computer via a USB interface. Two firms, one developing a computer and one developing a mouse are completely de-coupled. The interface specification provides all the information needed for coordination of the two firms. The complete de-coupling does not only allow for simultaneous development of the components but moreover makes the development autonomous in two respects. Firstly, firms autonomously decide upon the specification of their component, only limited by the standardized architecture. Secondly, firms do not need to interact before or after the development process. Whereas the first point is already achieved by adopting a modular architecture, the second point arises due to the standardization of the components. Due to the standard, firms may enter the market and develop products without the need to coordinate a priori with other actors on the market (see e.g. Matutes and Regibeau, 1996). The standard specification and market prices are sufficient to form expectations on the future prospects of the newly developed product. The point is that within a stable and public product architecture firms can form expectations on the future relevance of their research products and therefore autonomously decide what, when and how to develop components.[5]

Although vaccines are not standardized, firms specialized in vaccine components are

[5]For a similar line of thought on the need of ex ante coordination see Richardson (1972)'s account on firm interdependence due to 'close complementarity'.

relatively autonomous in their development decisions. They enter the industry without existing relationships to other firms and they form alliances to integrate components after having developed vaccine components (Bonah et al., 2007, p.228ff).

This is possible because industry participants share a common understanding of the vaccine architecture (Bonah et al., 2007, p.224). The actors are all embedded within the same scientific paradigm. Problem decomposition in science led to specialization in research and to the conception of a vaccine as a nearly modular product. This 'design process' is different from the one usually described in the literature on modularity which focuses on engineering design (see for example the review of Colfer, 2007). Whereas in engineering design, the product architecture is considered to be a decision variable (for example Brusoni et al., 2001; Sanchez and Mahoney, 1996; Ulrich, 1995; von Hippel, 1990), the vaccines architecture emerged from scientific progress.

Although vaccine components as well as respective organizations are not completely de-coupled, it seems appropriate to describe them as being loosely coupled. Components are loosely coupled because they are distinct and exchangeable to some extent. However, because interactions are not clearly understood the result of a novel combination of components remains uncertain. With respect to organizational modularity it is noticeable that the division of work in many alliances is rather clear cut, with an ex ante division of tasks and rather few joint research activities (Bonah et al., 2007, p.234). Distinct organizations are simultaneously and autonomously engaged in the product development process but need to respond to each other when integrating the components. Hence, besides product components, also organizations are loosely coupled.

In comparison to an integrated product architecture, a loosely coupled product architecture tends to offer similar advantages as a modular architecture. It may i) improve the product life cycle management, ii) make the organization of product development more efficient, iii) allow for simultaneous development of components, and iv) yield specialization effects. Furthermore, we observe that the novel product architecture allows for a division of research between firms.[6] The following section focuses on the question how modularization of the vaccine is reflected in the organization of the industry.

5.2.4 Technology Transfers between Firms

This chapter considers the division of labor among firms in the vaccine industry. Following Jacobides et al. (2006) and von Hippel (1990), the division of labor may be

[6] The question whether an integrated/modular product architecture is best (normative) or often (descriptive) mapped to an integrated/modular organizational architecture has a long tradition (see Colfer, 2007, for a recent review). The empirical literature suggests that a modular product architecture does not necessarily induce a modular organizational architecture but probably is a prerequisite.

characterized by the mapping of actors onto (a set of) tasks and the pattern of transactions between the actors. Assume that the technological specialization of firms as well as their resources are given. Furthermore, we may assume that firms try to exploit their comparative advantage and choose to perform those tasks to which their specialization fits best (Richardson, 1972). Then, the remaining question concerns the pattern of transactions between firms. This question is the focus of the empirical analysis in this chapter.

Before proceeding to the empirical analysis, this section discusses arguments to form expectations on the pattern of technology flow. First, we briefly consider the vertical division of work between integrated pharmaceutical firms and biotechnology firms. In a second step, biotechnology firms are further distinguished by their specialization into transversal technology firms and firms which are co-specialized on certain diseases. In a third step, it is discussed how the presence of firms specialized in vaccine components possibly affects the pattern of technology flow. Note that the discussion, as well as the empirical analysis, remains restricted to firms. Non-profit research organizations are not considered in the discussion because they have other incentives and are not in the analysis because of the problem to measure their competences. However, excluding non-profit research organizations does not change the pattern of technology flow among firms, which is the main interest here.

Transactions from Biotechnology Firms to Pharmaceutical Firms The previous literature on the division of innovative labor in the pharmaceutical industry first distinguished integrated pharmaceutical firms and new biotechnology firms (e.g. Arora and Gambardella, 1990). The division of work between these two firm types seems to be predefined by the distribution of resources. The integrated pharmaceutical firm typically has strong financial and organizational resources which are necessary for drug development and commercialization. The biotechnology firm is supposed to master better the new scientific methods which emerged during the biotechnology revolution. This fosters a vertical division of innovative labor. Integrated pharmaceutical firms cover all activities along the value chain with a focus on downstream activities, whereas biotechnology firms focus on research; the upstream activity in the value chain.

Transactions from Co-specialized and Transversal Biotechnology Firms A closer look on the pharmaceutical industry reveals that biotechnology firms might take very different roles in the industry (Pammolli, 2004). Some biotechnology firms develop transversal technologies which might be used in diverse applications; research as well as production. Other biotechnology firms focus on product development and co-specialize on a certain treatment of an indication. Differentiating between transversal technology firms and co-specialized firms leads to important insights. The firm types follow different business models and find themselves in different niches (Orsenigo et al., 2001).

Transversal technology firms face a large inter-industry market for their research tools and services because many firms potentially apply their proprietary technology. Licensing of a single technology to many industry actors may create an early stream of revenue and yield financial stability (Gambardella and McGahan, 2009). The situation is different for co-specialized firms. Co-specialized firms have fewer potential customers as their technology is not widely applicable. Actual distribution of their research on pharmaceuticals is furthermore limited by the need for exclusivity in drug development. A potential buyer only values high an exclusive license because large losses might incur if a competitor as well develops the drug and wins the race. Furthermore, co-specialized firms face the high risk of failure during product development. After spending large amounts of money and time the product might fail in one of the development stages. Nevertheless, profits might be very high later when the product turns out to be a success. In sum, transversal technology firms and co-specialized firms face different markets (wide and narrow), different risks (low and high) and different revenue streams (stable and loss/profit) (Gambardella and McGahan, 2009).

The study of Orsenigo et al. (2001) investigates how the different roles of transversal and co-specialized firms affect the network of alliances. They find that co-specialized firms tend to have few collaborations with integrated pharmaceutical firms which generates a hierarchical structure similar to a network tree. In contrast, transversal firms supply their technology to many firms, including integrated pharmaceutical firms as well as co-specialized firms. This alliance behavior has been found to interconnect the branches of the network tree and thereby fosters a less hierarchical network. Most alliances in the pharmaceutical industry include some kind of technology transfer, be it technological knowledge (e.g. research alliance) or property rights on technology (e.g. commercialization alliance). This leads us to largely equate the network structure with the pattern of technology flow. Therefore, based on the study of Orsenigo et al. (2001), we expect a technology flow from transversal firms to all other firms (integrated pharmaceutical firms and co-specialized firms) and a technology flow from co-specialized firms mainly to integrated pharmaceutical firms.

In the vaccine industry, one can distinguish at least two generic fields of expertise resulting in transversal technologies (Bonah et al., 2007). One field is cell cultures. Cells are used for production of vaccines as well as for cultivation of pathogenic agents, making cells a premise for research (Cells). The second field subsumes the various transversal technologies to identify and operate on the genetic code, e.g. recombination technology and diagnostics using proteomic and genomic platforms (Drug Discovery/Diagnostics). Both types of specialization, Cells and Drug Discovery/Diagnostics, will be distinguished in the subsequent analysis. In our case, co-specialized firms are firms which are specialized on vaccine components. The next paragraphs discuss their potential role in the industry in more detail.

Transactions for integration of components Recent technological developments in vaccines research enable a further division of labor. Besides co-specialized firms and transversal technology firms, we now observe firms which are specialized in components of a pharmaceutical product (in the following denoted also as "component firms"). This chapter argues that the more fine grained division of labor has been made possible by problem decomposition due to the biotechnological revolution.

A changing product architecture due to disruptive technological change allows for a (re-)definition of roles in the industry (Jacobides et al., 2006, p.1203). Therefore, a priori, it is not clear which roles the different firms take over and, hence, how the new division of work looks like. However, it is clear that specialization of firms in product components necessitates integration of components across firm boundaries. Hence, the role of the integrator need to be taken over by some firm(s). The question of who takes this strategic position determines to a large part the organizational architecture in the industry. There are strong reasons to believe that integrated pharmaceutical firms will act as systems integrators in the industry. However, the technological discontinuity which led to the modularization of vaccines might allow new biotechnology firms to take over this role. Let's consider briefly the arguments for both alternatives.

Pharmaceutical firms may have the motivation as well as the potential to act as systems integrator. Firstly, pharmaceutical firms have the motivation to in-source novel components because they are likely to realize high profits by i) exploiting the "mix-and-match" property of modular architectures (Ulrich, 1995) and by ii) employing their complementary resources for commercialization of novel vaccines (Teece, 1986). i) Modularization implies that novel components can be applied in several vaccines for different indications (see Ulrich, 1995, for a general discussion). Because pharmaceutical firms offer vaccines for several indications they are able to exploit economies of scope by introducing improved components in several of their product lines. For example the same adjuvant may be used in several vaccines. In addition individual vaccines may be continuously improved and diversified by exchanging or adding components. For example a further antigen might be added into an existing vaccine to extent indications. ii) Furthermore, pharmaceutical firms have an interest in developing novel vaccines because they have the complementary resources to successfully commercialize the innovation (Teece, 1986, p.288). Their established commercialization and distribution channels allow for fast recoup of development costs.

Secondly, pharmaceutical firms may have the capability to integrate. The study of (Brusoni et al., 2001) emphasizes that firms which integrate the external research efforts of specialized knowledge producers need to have a broad knowledge base. System integrators need to have architectural as well as component knowledge for both, integration and management of research efforts. Pharmaceutical firms are likely to have this knowledge base due to their own past and current research efforts in vaccines. Note that past experience probably includes not only traditional approaches of vaccine research, but also new scientific approaches in drug discovery (Cockburn and Henderson, 1998). In sum, the economic as well as technological arguments put forward so far support the view that pharmaceutical firms are most likely to take over the role of system integrators. This would result in a technology flow from all “component” firms to pharmaceutical firms.

On the other hand, there are also arguments that “component” firms are willing and able to act as systems integrator. Even though “component” firms do not have the commercialization and distribution channels, they might favor to integrate components themselves because the later the development stage of a product, the larger is the bargaining power of specialized firms with respect to integrated pharmaceutical firms. This is due to the high failure rate of new products in pharmaceutical research and development. There are vast research opportunities, many early stage efforts and very few late stage products (DiMasi et al., 2003). This pattern implies that the bargaining power of research firms is very low when trading early stage research efforts. From the point of view of the pharmaceutical firm, contracting with a specific research firm for early stage products is not a necessity. There are many other research firms offering a similar prospectus for a successful product. This puts biotechnology firms in a weak bargaining position. Market power is reversed for late stage products because late stage products are relatively scarce and strategically important for integrated pharmaceutical firms. For integrated firms, it is crucial to gain the commercialization rights of a novel product in order to keep up a high market share. This puts biotechnology firms in a strong bargaining position. Hence, they might appropriate a higher rent from their research efforts the later the development stage of the product.

Besides the incentive, “component” firms also might have the capability to integrate. The technological change which led to the modularization of vaccines might be an advantage for biotechnology firms which are more familiar with the new research regime than pharmaceutical firms. In the language of Henderson and Clark (1990), modularization might be competence destroying for pharmaceutical firms because a large part of their accumulated knowledge on traditional vaccines became obsolete under the new research regime. Having an edge in scientific research might trade-off for the more narrow knowledge base of “component” firms.

Given that “component” firms integrate components, the question remains which of the “component” firms is most likely to do so. Among others, this is going to depend on the bargaining position among component firms vis-a-vis each other as well as their technological competences. All three components, i.e. antigen, vector and adjuvant, are complementary to each other as each is needed for a vaccine. However, they differ in that antigen is specific to a certain indication whereas vector and adjuvant may be introduced in vaccines for several indications. Therefore, vector and adjuvant are more easily substituted than antigen when a novel vaccine is developed. The bargaining power of a firm is lower, the easier it is to substitute its input (Jacobides et al., 2006). This gives the antigen firm a stronger bargaining position as the vector and adjuvant firms. The technological argument is that antigen firms are specialized on the indication which the future vaccine is going to target. Evaluation and improvement of vaccines need to be done with respect to the illness and, therefore, also technological specialization of antigen firms is in favor of their potential role as systems integrator. In sum, antigen firms are most likely to act as system integrators and we expect that technology flow is directed from vector and adjuvant firms to antigen firms.

Transactions between firms of the same specialization So far we discussed potential relationships and associated technology flows between the different firm types. The question remains to what extent technology might be transfered between firms of the same type. To get an intuition, we start from the observation that research on vaccines entails many activities (see Baldwin, 2008, for this train of thought). Activities are interrelated to the extent that one activity depends on another activity. Interdependent activities need to be coordinated and, because the output of one activity serves as an input of another activity, something is transfered between the activities. Problem decomposition in pharmaceutical research in general and modularization of vaccine research in particular implies that activities cluster in sets of activities which are strongly interrelated. According to the definition of modules in complex systems by Simon (1962), these clusters are modules where interaction within modules is stronger than between modules. Baldwin (2008) argues that the modular structure of activities influences the division of work in the industry, i.e. the mapping of firms onto sets of activities. The mapping determines which activities are coordinated inside the firm and which activities are coordinated between firms. Next to the coordination it also determines the intra- and inter-firm flow of inputs and outputs of activities. From a transaction costs perspective, Baldwin (2008) argues that the boundaries of the firms are likely to match the module boundaries. In this case transaction costs associated with organization and transfer of inputs and outputs are low. Our typology of firm types rests on the firm's technological specialization in modules. Building on Baldwin's argument, we expect that firms cover rather self-contained sets of activities which allow for the production of complete components and not only parts of it. Therefore firms of one module are not likely to be in symbiotic interdependence but rather to be in competition. The final conclusion is that firms of one module are unlikely to cooperate and, hence, we expect a weak technology flow among firms having the same specialization (BurethPenin).

Summary Table 5.1 summarizes the pattern of technology flow as implied by the discussion of firm interdependence. The expected network is strongly hierarchical. In particular, integrated pharmaceutical firms with diverse competences in vaccines (in the following also 'diverse' firms) are expected to receive technology from all other participants; indicated by entries of one in the first column of table 5.1. Two arguments justify this expectation. Firstly, the distribution of technological, organizational, and economic resources over biotechnology and integrated pharmaceutical firms implies a vertical division of labor in the pharmaceutical industry. Secondly, pharmaceutical firms are also likely to integrate vaccine components because they have a broad knowledge base and are able to exploit the benefits of (modular) product development.

Technology flow among biotechnology firms also is expected to be hierarchical. It has been argued that specialized biotechnology firms have a stronger bargaining position vis-a-vis pharmaceutical firms, the more their product is developed. This gives specialized "component" firms the incentive to develop vaccines by integrating components. Because adjuvants and vectors are more easily substituted than antigen, antigen firms are most likely to act as integrators. This led us to expect that there is a technology flow from adjuvant and vector firms to antigen firms.

Firms specialized in transversal technologies are expected to follow a business model in which they supply all other firms with generic technologies. Finally, strong cooperation among firms with the same specialization is not expected because high transaction costs prevent cooperation within modules. The discussion above neglected the role of other firms and actors in the industry, which are subsumed in the remainder category "Other" in table 5.1.

Table 5.1: *Expected technology flow between firm types* [a]

From \ To	Diverse	Antigen	Adjuvant	Vector	Diagnostic	Cell	Other
Diverse	.	0	0	0	0	0	.
Antigen	1	0	0	0	0	0	.
Adjuvant	1	1	0	0	0	0	.
Vector	1	1	0	0	0	0	.
Diagnostic	1	1	1	1	0	0	.
Cell	1	1	1	1	0	0	.
Other	.	.	.	.	.	.	.

[a] 1/0 indicates high/low technology flow respectively, (.) indicates no expectation.

5.3 Pattern of Technology Flow

The previous section developed a theoretical image of the pattern of technology flow among firms of the vaccines industry. This section investigates to what extent the empirical technology flow among firm types corresponds to the pattern of technology flow as implied by the theoretical discussion. The first subsection presents the sample which consists of French vaccine firms as well as their collaborators. The data yields the directed technology flow among firm types. The second subsection develops a testing strategy and discusses two exact tests. Both tests assess to what extent the observed pattern of technology flow systematically complies with the theoretical discussion. Testing results are presented in the last subsection. Whereas the central role of pharmaceutical firms is strongly confirmed, results are largely inconclusive with respect to the pattern of technology flow among biotechnology firms. Therefore, an analysis of the in- and out-sourcing behavior of individual firms follows in the next section.

5.3.1 Sample

The previous section developed a theoretical image of the network among firms active in the vaccines industry. This section derives and describes the sample used for assessing the empirical relevance of this image. Before going into the details of the sampling process, an overview is helpful: the sample is a dynamic network among firms and other institutions active in the pharmaceutical industry, reconstructed for the years 1994 until 2006 inclusive. The sample population is derived in a two step snowballing procedure; starting with a nucleus of French vaccine actors, all their partners in vaccine alliances are included in the population. The entities in the sample population are characterized by their technological competences along the categories derived in the previous sections. Information on entry and exit, partly due to Mergers and Acquisitions, is used to reconstruct the dynamics within the population from the year 1994 until the year 2006. Alliances between members of the population for these years are collected. The alliances are categorized into alliances which have or have no vaccine content. For those with vaccine content, the direction of technology flow is identified. This provides the information on directed vaccine alliances among firms with specific technological characteristics needed for the analysis in the next section.

The sample is based on a two step snowballing procedure. In a first step, the nucleus of the network is formed by all French organizations active in research on vaccines in 2005. These organizations form the nucleus because it is a well defined sub-population of the vaccine industry and detailed information from previous research is readily available (Bonah et al., 2007). In 2005, the French vaccine sector consisted out of 28 entities: 22 small/medium biotechnology firms, three big pharmaceutical firms and two research institutions (Bureth et al., 2007). Some of the firms have predecessors which are also included into the list of nucleus organizations, yielding a total of 34 legal entities. Over time, these entities have been engaged in formal agreements with firms, universities/public research institutes and other institutions. Their agreements have been collected from three sources: interviews, the recap database (www.recap.com, accessed 2007) and the firms websites. These alliances are used to expand the population in a second step. In the second step, the collaboration partners of the French firms extend our panel. In order to remain in the vaccine industry, a firm is added if the respective agreement has some vaccine content (i.e. considers a vaccine product or a method potentially connected to vaccines), or the agreement changes the ownership structure of the panel companies (e.g. an acquisition). This step yields another 145 international players, 123 of them being firms. The firms enter and complete the sample consisting of 157 firms (131 biotechnology firms and 26 integrated pharmaceutical firms).

The categorization describes competences with respect to the functional elements of a vaccine, i.e. *antigen*, *vector* and *adjuvant* as well as the more generic competences *cells* and *drug discovery / diagnostics*. A specific technological competence has been assigned to a firm, if it is one of its main competences. Integrated pharmaceutical firms with diverse competences in research for vaccines have been coded *diverse*. Pharmaceutical firms with little competence in vaccines, signaled by few research and commercial commitment, are coded *other drug*. For some firms, coded *n.a.*, competences could not be defined. For the analysis *other drug* and *n.a.* are both joined within the category *other*.

The identification of categories results for 28 cases from interviews. All other assignments are based on public information, mostly the firms' web sites but also their patents, and have been assigned by myself or other economists of our institute. Some assignments called for judgment by the researcher. In these cases we discussed and searched further indications. Although such assignment procedures can not be fully objective, the joint effort increases reliability of the data. The assignment is based on observations in 2006 and earlier, if the firm exited before. Because detailed historical data is not available, the assignment of technological competences is largely static. Changes in a firms technological competence are solely caused by mergers and acquisitions, where one firm is completely absorbed by another firm. In those cases, it seems plausible that the acquiring firm acquires the competences of the acquired firm. This results in accumulation of research fields for all firm types except pharmaceutical firms with with diverse competences in vaccine research (coded *diverse*) which have been defined as being knowledgeable to some extent in all specialization fields. The identification of categories yields one category for 132 firms, two categories for 22 firms and three categories for 3 firms. We observe about 20 firms in each of the categories, except for the 'cell' competence where we observe 8 firms. Furthermore, there are 8 firms to which no category could be ascribed. The appendix D provides a table which summarizes the result of the categorization.

Mergers and Acquisitions led to changes in the population. Within the years 1994 and 2006, we observe 11 mergers and acquisitions among panel firms. The network is accumulated in such a way that the successor takes over all alliances of its predecessor. Firms enter the network when they are founded as isolates. In case the founding date is not known, they enter with their first alliance. Entry and exit in combination with mergers and acquisitions results in a population which changes over time. Basic statistics on population dynamics and the alliances are provided in the appendix D.

The firms in the population and their antecedents had various alliances over time. Most of the alliances observed are taken from the recap database (recap 2007). The recap database gives, among others, the date of agreement and a description of the alliance content. Based on the alliance description given by recap and public firm announcements, alliances are indicated as having vaccine content or not. For most of the vaccine alliances a direction of technology flow from one partner to the other partner could be assigned. In case of licensing, the donor and receiver of the product can be clearly identified. But also in collaboration agreements often it is possible to determine the respective roles. Mostly, one partner brings in a technology developed until a certain stage and the other partner takes over the technology for further development and exploitation (see also for example Orsenigo et al., 2001). In cases where both partner exploit the results of collaboration, the technology flow is in both directions weighted by one half.

Turning to the alliances, table D.3 shows that the number of alliances has been increasing over the years, from 9 alliances in the year 1994 up to 30 alliances in the year 2006. Vaccine alliances take a share of around 80%, with most of them being directed. In total, we observe 225 directed vaccine alliances. Firms are involved in directed vaccine alliances to a differing degree. The firms' number of alliances ranges between 0 and 45 alliances with an average of 2.8 alliances. Out of 131 firms in 2006, 22 firms of the sample have no directed vaccine alliance, 48 firms have one directed vaccine alliance and 61 firms have two or more directed vaccine alliances.[7] The number of in- and out-sourcing alliances per firm are similarly skewed.

Table 5.2 shows which firm types delivered technology to which other firm types in directed vaccine alliances. This table reveals that *diverse* firms function in most alliances as receiver of technology from all firm types; integrated pharmaceutical firms in-source technology in 113 out of the 225 alliances. The role of the other firm types is less clear because the number of firms in each category varies over years. Therefore, the analysis in the next section provides some further insights.

5.3.2 Testing Strategy

The observed firm type interaction, aggregated over years, is given in table 5.2 and the hypothesized firm type interaction, independent of time, is given in table 5.1. Now, we would like to know: is the observed firm type interaction random, or is it systematically influenced by firm interdependence as hypothesized in the ideal image of table 5.1?

This question can be answered by following the methodology of exact tests. We assume that the observed network is one possible realization of a random network formation process. Under the null hypothesis, firm types are irrelevant for alliance formation. This allows us to define a set of comparable random networks, the reference set of random networks, which could have been realized as well under the null

[7]The description of the alliance activity of firms is based on the alliance activity over years but for the consilidated set of firms at the end of 2006.

Table 5.2: *Frequencies of directed vaccine alliances* [a]

From \ To	Diverse	Antigen	Adjuvant	Vector	Diagn.	Cell	Other	$\sum$ Supply
Diverse	5.0	2.8	1.5	0.4	1.2	0.2	4.0	15.0
Antigen	21.4	10.2	2.2	1.9	0.7	0.7	3.1	40.1
Adjuvant	10.9	2.2	1.9	0.5	1.6	0.2	3.8	21.1
Vector	15.3	5.9	0.9	2.5	1.0	0.5	3.1	29.2
Diagnostic	29.1	5.5	2.0	2.1	5.2	0.8	7.8	52.5
Cell	11.2	6.2	1.2	1.5	0.7	2.0	2.2	25.1
Other	20.0	6.6	1.6	4.5	3.8	0.6	5.0	42.0
$\sum$ Source	113.0	39.2	11.2	13.4	14.2	4.9	29.0	225.0

[a] Calculated on a year-wise basis and aggregated over years 1994-2006.

hypothesis. All networks of the reference set share features which are considered to be invariant and influential for the aspect of the network we are interested in. Two important features are for example the number of firms in each category and the overall number of alliances in the network. The reference set of random networks allows a comparison of the observed firm type interaction with the distribution of firm type interactions resulting within the reference set of random networks. The comparison enables us to deduce whether the observed firm type interaction is significantly unusual and therefore can be assumed to be non-random in the hypothesized way.

More formally, let the aspect of firm type interaction we are interested in be captured by the test statistic $T(\boldsymbol{y})$, which is calculated on the network $\boldsymbol{y}$. Under the null hypothesis of irrelevance of firm types, the observed network $\boldsymbol{x}$ is assumed to be one realization from a set of random networks. The set of random networks is constructed by defining invariant features shared by all networks of the set. The exact probability of observing a test statistic equal to or more extreme than $T(\boldsymbol{x})$ is the sum of all probabilities over those networks which yield such extreme test statistics ($\sum_{\boldsymbol{y}:T(\boldsymbol{y})\geq T(\boldsymbol{x})} Pr(\boldsymbol{y})$). The sum over probabilities equals the significance level of rejection of the null hypothesis. In the following, we assume that networks are uniformly distributed, i.e. that each network of the reference set has the same probability of being realized. Then, the significance level of rejection equals the fraction of networks with "high" test statistics in the set of comparable networks.

In order to proceed we need to define an appropriate test statistic and an appropriate reference set of random networks. Finally, because enumeration of all networks within the reference set usually is not practicable, we need to obtain a uniformly distributed sample of the reference set of random networks in order to approximate the distribution of the test statistic. These steps are discussed in the following.

The hypothesized ideal image provides a joint hypothesis with respect to the overall pattern of firm type interaction (the pattern of zero-one entries) as well as hypotheses regarding the interaction among each two firm types (single entries in each cell of the table). The test statistic needed for the joint test necessarily differs from the test statistic used for single hypotheses.

Single hypotheses concern the interaction of two specific firm types i and j. For those firm type combinations ij which are coded as one (zero) in the hypothesized ideal image, we would like to know whether we observe more (fewer) alliances than expected by chance. The share of alliances falling into the respective firm type combination is an appropriate test statistic. Therefore, we define for single hypothesis testing the test statistic $T_{ij}(\boldsymbol{y}) = f_{ij}(\boldsymbol{y}) \,/\, N(\boldsymbol{y})$, where $f_{ij}(\boldsymbol{y})$ is the ij'th entry in the firm type interaction table of network $\boldsymbol{y}$ and $N(\boldsymbol{y})$ is the number of alliances in the network.

The single hypotheses are one sided. For those firm type combinations where the hypothesized ideal image displays a one, we expect many alliances. Under the uniform distribution assumption, the significance level of rejection equals the share of networks from the reference family of random networks which displays a higher frequency of respective firm type interactions than observed in the sample. When firm type combinations in the ideal image are coded as zero, we expect few alliances and, accordingly, count the number of networks which display fewer firm type interactions.

Another test statistic is needed for the joint hypothesis. The joint hypothesis states that the observed network among firms is associated with the overall hypothesized pattern of firm type interaction. A simple and yet meaningful test statistic is the share of alliances falling into those firm type combinations which are assumed to be interdependent. More formally, we choose the test statistic $T(\boldsymbol{y}) = \sum_i \sum_j \, d_{ij} \, f_{ij}(\boldsymbol{y}) \,/\, N(\boldsymbol{y})$, where the sums are over all firm type combinations ij, d_{ij} is the entry in the hypothesized firm type interaction matrix, $f_{ij}(\boldsymbol{y})$ is the entry in the firm type interaction table of network $\boldsymbol{y}$ and $N(\boldsymbol{y})$ the number of alliances in the network. [8]

[8] Whereas the hypotheses are stated on the level of firm types, the principle unit of observation is the network of alliances between firms. Therefore, test statistics are calculated on the level of the network among firms (i.e. based on the adjacency matrix representing alliances among firms) or on the level of firm type interaction (i.e. based on the firm type interaction matrix). In the former case one needs to map the hypothesized firm type interaction on the population of firms and derive a hypothesized network among firms. In the latter case one needs to map the network among firms on the firm types. Because the latter is non-injective one might consider whether there is some loss of information. In particular, in case the observed network among firms is weighted, the non-injective mapping causes the loss of information on the variance of firm interaction. However, this is not a problem when we handle binary adjacency matrices. Therefore, we derive test statistics on the level of firm type interaction which lead to exactly the same ranking of networks as obtained by similar appropriate test statistics on the level of firms. For example, the test statistic proposed yields the same ranking of networks as does the correlation of the hypothesized matrix of alliances with the empirical matrix of alliances (as long as the network density within the set of comparable networks is fixed). To see this, assume there is an empirical network $\boldsymbol{y}$ and another network $\boldsymbol{y}'$ with only one link being different. Both are correlated with the hypothesized firm network $\boldsymbol{h}$ such

For deciding on the reference family of random networks, it is important that the ideal image of firm type interaction reflects two types of firm interdependence. The first type is the interdependence between large integrated pharmaceutical firms and small specialized biotechnology firms due to the separation of financial and technological resources. This kind of interdependence led to the hypothesis that *diverse* firms occupy central positions in the network, being the sinks of technological flow. Note that strong interdependence is assumed with all other firm types and no difference is made between different types of specialized firms. In the ideal image of firm type interaction, this is reflected in the entries of the first column being all one. Thus, the focus of this hypothesis is on the position of *diverse* firms in the network, characterized by the frequency of in-sourcing alliances irrespective of firm types.

The second type of interdependence is assumed among specialized biotechnology firms due to the separation of different fields of technology and their use and interplay within the value chain. This kind of interdependence led to the hypotheses that specific firm type interactions are more likely to occur than others. For example we expect a higher technology flow from *vector* firms to *antigen* firms than to *adjuvant* firms because of the central importance of the antigen function in a vaccine. Such considerations imply a certain pattern in partner choice (e.g. *vector* firms delivering rather *antigen* firms than *adjuvant* firms).

To summarize, financial-technological interdependence rather yields hypotheses on the frequency of alliance formation whereas inter-technological interdependence rather yields hypotheses on the pattern of partner choice. This can be taken into account in hypothesis testing. Different constraints on random networks define the set of comparable random networks which allows for testing frequency and pattern of alliance formation jointly or for testing only pattern of alliance formation.

First one may restrict to all networks which have exactly the same (graph) structure with the only random element being that firms are randomly assigned to nodes. Using this set of random graphs allows for testing whether firm types are associated with the firms' network position. Because the firm's network position results from frequency of alliance formation and pattern of alliance formation, such a reference distribution yields a joint test on the relevance of firm types for frequency and pattern of alliance formation. The advantage of this approach is that no assumptions additional to the irrelevance of firm types need to be employed. Especially no further assumptions regarding the network formation process are introduced, because all networks of the reference distribution display the same graph structure. The disadvantage is that the contribution of rate and pattern to the significance result can not be distinguished. In testing for alliance formation implied by firm interdependence this creates a problem,

that $Cor(\boldsymbol{y}, \boldsymbol{h}) < Cor(\boldsymbol{y'}, \boldsymbol{h})$. Because density is fixed in the binary adjacency matrix, mean and variance of the adjacency matrices of $\boldsymbol{y}$ and $\boldsymbol{y'}$ are equal. Therefore, any change of an alliance which causes higher correlation of $\boldsymbol{y'}$ is going to change the firm type interaction matrix as well.

because frequency of alliance formation of firm types may differ for other reasons than interdependence.

Therefore, it is reasonable to specify a second reference family of random graphs by restricting the in- and out-going alliances for all firms to be the same as in the observed network. Fixing the frequency of alliance formation allows only partner choice to be random. Hence, only the irrelevance of firm types for partner choice is tested. The advantage is that the frequency of alliance formation is controlled for completely. Besides losing the aspect of frequency of alliance formation, one disadvantage is the implicit assumption of independence of alliance formation during network formation; each network with the same distribution of in- and out-going ties is assumed to be equally likely irrespective of further structural characteristics.

In the following, we provide hypothesis tests for each of the family of random graphs discussed. However, for neither family of random graphs exact statistics can be obtained because it is not practicable to enumerate all their members. Therefore, testing is based on a uniformly distributed sample of the set of random graphs which is obtained by Monte Carlo techniques.

For the first reference family of random graphs, a sample of random networks having the same structural properties as the observed network is drawn by applying the Quadratic Assignment Procedure (QAP). Within the QAP, firm types observed in the population are randomly assigned to firms. For static networks, which are represented by a single adjacency matrix, drawing a uniform sample of random networks is simple. One random draw is obtained by random permutation of the firm labels. However, our case is more complicated because we observe a dynamic network with changing population and varying firm types ascribed to firms. Simply permuting the firm labels within the adjacency matrix of each year would not respect the evolution process of the network which causes ascribed firm types to vary over time. In our setting it is more appropriate to permute the firm types initially ascribed to firms. Therefore, one draw from the reference family is obtained by random permutation of the firm types initially ascribed to firms, letting the network evolve over years as described in section 5.3.1, extract the year wise adjacency matrices and calculate the firm type interaction matrix aggregated over years.

The second reference family of random graphs are all networks with the same row and column sums as the observed network. Because firm identities as well as their frequency of alliance formation are fixed, network evolution need not to be considered. One draw from the reference family is obtained by drawing one random adjacency matrix for each year and aggregating them. Due to the procedure, the test is called "adjacency matrix permutation test" in the following. The sample is obtained with a Markov Chain Monte Carlo (MCMC) algorithm developed by Verhelst (2008), which is implemented in R in the package *RaschSampler*. This MCMC sampler converges towards a uniform stationary distribution of random networks of the family of zero-one-matrices with given marginals. Important parameters for the MCMC algorithm are the burn-in period, i.e. the number of steps until convergence to stationary distribution should be reached and the step size, i.e. the number of steps between two consecutive draws in order to avoid correlation between draws. They are set large enough so that further increase does not change the result.

5.3.3 Results

The QAP test and the adjacency matrix permutation test in combination yield the following results. The hypotheses on technology flow from biotechnology firms to pharmaceutical firms is strongly supported by the data. The hypotheses on the hierarchical relationship among biotechnology firms is weakly supported. In particular, the data does not show a triadic configuration, where adjuvant and vector firms supply technology to antigen firms. However, as hypothesized, technology flow between adjuvant and vector firms is weak and antigen firms seem to integrate components for development of vaccines. The following discussion first focuses on the QAP test results and then on the adjacency matrix permutation test results. Both tests complement each other by focusing on different aspects. A summary is given at the end of this section.

QAP test Consider first the QAP test results in table 5.3. This permutation test assumes that the observed pattern of technology flow among firm types is simply determined by the structure of the alliance network in combination with the number of firms of each specialization. The null hypothesis is that firm types are not associated with the pattern of technology flow. Under the null hypothesis, a random permutation of firm labels is likely to yield a pattern of technology flow which is similar to the observed one.

The joint test of irrelevance of firm categories for the pattern of technology flow is rejected at a significance level below 0.1%. This means that 99.9% of all permutations result in a technology flow among hypothesized firm type combinations which is weaker than actually observed.[9]

The high significance of the joint QAP test is largely due to the central role of pharmaceutical firms with *diverse* competences in research on vaccines. These firms insource technology from all biotechnology firms at a significantly high rate (indicated by significant entries in the first column of table 5.3). This result has been expected from the hypotheses. However, the literature discussion provides two explanations. The first is the vertical division of labor due to financial and technological interdependence. The second is the potential role of pharmaceutical firms as system integrators. To what extent the latter argument holds is not answered by the test. The case of Sanofi Pasteur, presented in the next section, however, suggests that the strong technology flow is at least partly caused by integrating activities of pharmaceutical firms.

[9]Hypothesized firm type combinations are indicated by entries of one in table 5.1.

Table 5.3: *Quadratic Assignment Procedure (QAP) test results* [a]

From \ To	Diverse	Antigen	Adjuvant	Vector	Diagnostic	Cell	Other
Diverse	2.22 0/2.04/4.89	1.22 0.67/2.59/5.11	0.67 0.37/1.98/4.22	0.19 * 0.44/2.1/4.67	0.52 0.44/2.21/4.89	0.07 0/0.92/2.52	1.78 0.44/2.58/5.56
Antigen	9.52 * 0.56/2.7/6.04	4.52 0.86/3.16/6.04	0.96 0.59/2.49/5.19	0.83 0.81/2.65/5.3	0.31 * 0.67/2.66/5.7	0.3 0.11/1.15/2.78	1.37 1/3.19/6.39
Adjuvant	4.85 * 0.37/2.03/4.59	0.96 0.57/2.47/5.19	0.85 0.22/1.8/4.22	0.22 * 0.44/2.09/4.76	0.7 0.3/2.02/4.44	0.07 0/0.89/2.37	1.7 0.44/2.4/4.9
Vector	6.81 * 0.26/2.2/4.74	2.61 0.74/2.64/5.09	0.41 * 0.44/2.12/4.56	1.11 0.33/2.11/4.67	0.46 * 0.48/2.14/4.54	0.22 0.07/0.97/2.67	1.37 0.74/2.68/6
Diagnostic	12.93 * 0.44/2.29/5.22	2.43 0.78/2.62/4.93	0.89 0.48/2/4.48	0.94 0.44/2.27/5.02	2.3 0.3/2.11/4.67	0.37 0/0.95/2.57	3.48 0.44/2.7/5.81
Cell	5 * 0/0.97/2.74	2.78 * 0.19/1.19/2.61	0.52 0/0.9/2.28	0.67 0/1.04/2.67	0.33 0/0.97/2.54	0.89 0/0.38/1.14	0.96 0.11/1.14/2.89
Other	8.89 * 0.44/2.6/5.78	2.93 0.81/3.15/6.16	0.7 0.44/2.29/5.33	2 0.67/2.69/5.59	1.67 0.59/2.59/5.52	0.26 0/1.15/3.26	2.22 0.44/3/6.22

[a] Cell entries display observed (simulated 5-percentile/average/95-percentile) frequencies by total number of alliances. * denotes significance at 5% rejection level of one-sided test. Significance level of joint hypothesis is below 0.1%. Results are based on 400 simulations.

The QAP test yields also significant results on technology flow among specialized biotechnology firms. Notably, technology flow between vector and adjuvant firms is weak (see entries *vector-adjuvant* and *adjuvant-vector* in table 5.3). This finding is coherent with the arguments put forward in the last section. Recall that both technologies are more easily substituted than antigens. This puts adjuvant and vector firms in a weak bargaining position to in-source antigens. However, both technologies are complementary only when joint with an antigen and, therefore, weak technology flow between these two firm types has been expected.

Furthermore, as hypothesized, technology flow is directed from transversal biotechnology firms to co-specialized biotechnology firms. Significant are the strong technology flow from *cell* firms to *antigen* firms as well as the weak technology flow from *antigen* firms and *vector* firms to *diagnostic* firms (see entries *cell-antigen*, *antigen-diagnostic*, and *vector-diagnostic* in table 5.3).

However, for interpretation one needs to keep in mind that within the QAP test the firms' rate of alliance formation plays a role. Assume for example that firms of two firm categories have a very high rate of alliance formation relative to other firms. Assume further that all firms choose randomly firms as alliance partners, irrespective of specialization. Then, the QAP test may find technology flow among the two firm categories having a high rate significantly strong; solely because of their high rate of alliance formation. The arguments which support the hypothesized pattern of technology flow among biotechnology firms mostly ignore how much technology actually is transfered but focus on to whom technology is transfered. The adjacency matrix permutation test controls for the firms' rate of alliance formation. Therefore, it is appropriate to discuss the relationships among biotechnology firms with the results of the adjacency matrix permutation test in view.

Adjacency matrix permutation test Results of the adjacency matrix permutation test are given in table 5.4. This test assumes that the observed pattern of technology flow simply results from the specialization of each firm in combination with its rate of alliance formation. The null hypothesis is that partner choice is independent of firm specialization. Keeping fixed the number of in- and out-going alliances for each firm, the test informs on the relative importance of firm specialization in technology sourcing and supply.

The joint hypothesis test is significant at a rejection level of 10.5%. This means that we observe in 10.5% of permutations with random partner choice more directed alliances which are in accord with the hypotheses than are in the sample. Thus, the null hypothesis of random partner choice can not be rejected with high confidence.

Nevertheless, some technology transfers between firm categories are significant. Significant entries in table 5.4 suggest that i) pharmaceutical firms are unlikely to source technology from other pharmaceutical firms (see entry *diverse-diverse*), ii) pharma-

Table 5.4: *Adjacency matrix permutation test results* [a]

From \ To	Diverse	Antigen	Adjuvant	Vector	Diagnostic	Cell	Other
Diverse	2.22 * 2.67/3.96/5.33	1.22 0.44/1.35/2.37	0.67 0/0.46/1.04	0.19 0/0.46/1.11	0.52 0/0.56/1.33	0.07 0/0.27/0.7	1.78 0.44/1.39/2.67
Antigen	9.52 8.15/9.79/11.56	4.52 * 1.85/2.95/4.07	0.96 0.41/1.05/1.85	0.83 0.59/1.3/2.11	0.31 * 0.37/1.07/1.89	0.3 0.06/0.37/0.78	1.37 * 1.48/2.58/3.78
Adjuvant	4.85 3.63/4.98/6.37	0.96 0.7/1.54/2.52	0.85 0/0.43/1	0.22 0.07/0.58/1.22	0.7 0.11/0.62/1.26	0.07 0/0.18/0.56	1.7 0.44/1.32/2.37
Vector	6.81 4.44/6.01/7.44	2.61 1.53/2.55/3.65	0.41 0.22/0.71/1.33	1.11 0.26/0.94/1.63	0.46 0.15/0.76/1.52	0.22 0.05/0.31/0.63	1.37 1.04/2.02/3.11
Diagnostic	12.93 * 8.44/10.69/12.78	2.43 * 2.9/4.34/5.83	0.89 0.52/1.25/2.1	0.94 0.74/1.59/2.59	2.3 0.67/1.63/2.81	0.37 0.15/0.52/0.96	3.48 1.78/3.27/4.78
Cell	5 3.89/5.2/6.52	2.78 1.2/2.06/3	0.52 0.12/0.44/0.91	0.67 0.15/0.65/1.19	0.33 0.22/0.82/1.44	0.89 * 0/0.3/0.67	0.96 0.67/1.61/2.59
Other	8.89 8/10.02/12.44	2.93 2/3.36/4.74	0.7 0.22/0.81/1.52	2 0.22/1.18/2.22	1.67 0.67/1.68/2.78	0.26 0/0.47/0.96	2.22 0.89/2.48/4

[a] Cell entries display observed (simulated 5-percentile/average/95-percentile) frequencies by total number of alliances. * denotes significance at 5% rejection level of one-sided test. Significance level of joint hypothesis is 6.6%. Results are based on 400 simulations.

ceutical firms are likely to source from *diagnostic* firms (see entry *diverse-diagnostic*, iii) technology sourcing among *antigen* and *diagnostic* firms is weak in both directions (see entries *antigen-diagnostic* and *diagnostic-antigen*), and iv) *antigen* firms as well as *cell* firms are likely to partner with firms having the same specialization (see entries *antigen-antigen* and *cell-cell*). Each of these outcomes is discussed in the following.

i) Technology transfers among pharmaceutical firms are rare, given their overall alliance activity. One explanation might be that pharmaceutical firms among themselves are in competitive interdependence which induces alliance formation to a lesser extent than symbiotic interdependence.

ii) Symbiotic interdependence is likely to induce the significantly strong technology flow from *diagnostic* firms to pharmaceutical firms. Taking into account more detailed information from the recap data base and companies' newsletters on the alliances confirms that the strong technology flow is mainly due to supply of diagnostic kits and other research tools from *diagnostic* firms to pharmaceutical firms. This observation attests to the pharmaceutical firms' strong in-house research efforts focused on product development.

iii) Technology flow from *antigen* firms to *diagnostic* firms is significantly weak, given their overall involvement in technology transfers. This has been expected on the consideration that technology flow is directed from upstream to downstream firms. The relatively weak supply of *diagnostic* technology to *antigen* firms is not explained easily. From a technical point of view one may state simply that *antigen* firms are more apt to source technology from other firm types.[10]

iv) Finally, we observe a significant number of technology transfers within the group of *antigen* firms and *cell* firms. This is in contrast to the hypotheses. The argument for not expecting within-group technology flow was that transaction costs for technology transfer between firms are low across module boundaries but high within modules. Therefore, it was expected that firms do research on technologies of their fields rather self-contained and deliver their output as an input for research to firms of other fields. The question is to what extent the empirical observation argues against this reasoning. Because the number of alliances is relatively small, it is reasonable to investigate additional information on these alliances. Additional information has been collected from the recap database and the companies' press releases as well as SEC filings.

First, we focus on the technology flow among firms with *antigen* specialization. The entry in table 5.2, which presents the technology flow among firm types, assigns a value of 10.2 to technology flow from *antigen* to *antigen* firms. The number is rational because each alliance is assumed to have an overall weight of one which is split equally over all the technologies of a multi-technology firm. In fact, the entry of 10.2 in table 5.2 is caused by 17 alliances among (multi-technology) firms with *antigen*

[10] Specifically the supply of *cell* technology, the second group of generic technologies, to *antigen* firms has been found to be significantly strong in the QAP test.

specialization. Out of these 17 alliances, only six alliances are among firms which are only specialized in *antigen* and in eleven alliances firms with multiple specialization are involved. Therefore, the alliances focus not only on *antigen* technologies. In particular, the alliances govern the transfer of four antigens, two adjuvants, two vectors, and one cell technology. Furthermore four alliances govern manufacturing agreements or extramural research and for three alliances no detailed information is available.[11] None of these alliances is actually a joint research project to develop an antigen but all focus on complete products by joining complementary technologies. Thus, we may conclude that the high interaction among antigen firms is not counter to the argument that technology transfers are mostly across modules. Rather, the result confirms the hypothesis that *antigen* firms are susceptible to act as system integrators.

Also, technology transfers among *cell* technology firms do not actually target development of cell lines. The technology flow of 2 among *cell* firms in table 5.2 is due to seven alliances including firms with multiple specialization. Six out of seven alliances consider licensing of two widely applied cell lines.[12] In these alliances, interaction among firms is weak. Therefore, the significantly strong technology flow among *cell* firms is not counter to the argument that transaction costs are high within module boundaries. However, the data also does not support that firms having the same specialization act as competitors and, therefore, are unlikely to transfer technology.

Summary We may summarize the main results of both tests in four points. Firstly, pharmaceutical firms with *diverse* competences in vaccine research in-source technology from all biotechnology firms at a high rate. They are central, downstream in the industrial network. This is confirmed by significant entries in the first column of table 5.3.

Secondly, the hypothesized hierarchical configuration among the three component firms is not clearly supported by the data. The hypothesis was that *adjuvant* and *vector* firms supply technology to *antigen* firms but not to each other. Contrary to expectations, *adjuvant* and *vector* firms are not particularly likely to supply technology to *antigen* firms (see table 5.4). However, technology flow among *adjuvant* and *vector* firms is weak as expected. This is confirmed by significantly few technology transfers in the QAP test, table 5.3, and is also visible but not significant in the adjacency matrix permutation test, table 5.4. Furthermore, *antigen* firms are susceptible to transfer technology among each other (see table 5.4). A closer look on these alliances suggests that within-group interaction among *antigen* firms is due to the integrating activities of *antigen* firms.

[11] It is at least notable that only in three alliances firms supply technology which is not considered to be their main competence. This supports the assumption that, in principle, the content of technology flow corresponds to the firm's specialization.

[12] In the seventh alliance an antigen is supplied by a firm with specialization *antigen* and *cell*.

Thirdly, technology tends to flow from biotechnology firms with transversal technologies to biotechnology firms specialized in components and not vice versa. The QAP test assigns significance to the weak technology flow from *antigen* and *vector* firms to *diagnostic* firms. The adjacency matrix permutation test assigns significance to the weak technology flow from *antigen* firms to *diagnostic* firms. However, also technology flow from *diagnostic* firms to *antigen* firms is significantly unlikely (see table 5.4).

Fourthly, the hypothesis that few technology transfers take place among firms having the same specialization is not confirmed. Within-group interaction is particularly strong among antigen firms as well as among cell firms, being significant in the adjacency matrix permutation test. Furthermore, *adjuvant*, vector and diagnostic firms tend to partner among each other. This however is not significant.

For interpretation, note that the interdependence between integrated pharmaceutical and biotechnology firms is strongly supported, whereas evidence for the hypothesized hierarchical technology transfer among biotechnology firms is weak.

5.4 Firm Cases

The previous analysis investigates the technology flow among firm types. The analysis confirms that the group of integrated pharmaceutical firms takes a central position by in-sourcing technology. However, technology flow among specialized biotechnology firms is relatively weak and the pattern between firm types is not very strong. This section considers the alliance behavior of two individual firms in order to better understand and interpret these results.

The central position of integrated pharmaceutical firms is in accord with the literature discussion. However, the literature discussion builds on several arguments. In order to gain a better intuition on how to interpret our results, we consider the alliances of one pharmaceutical firm, Sanofi Pasteur. We find that this company indeed exploits the benefits of modular design and acts as an integrator of vaccine components.

The diffuse pattern of technology flow among specialized biotechnology firms had not been expected from the discussion of the literature. The case of Crucell, a biotechnology firm with multiple competences, helps to better understand this result. This case shows that in general the arguments invoked in the literature discussion hold. However, it also suggests that the type of technological specialization does not predetermine the business model followed by the firm, which was an implicit assumption in the literature discussion in section 5.2.

5.4.1 The Case of Sanofi Pasteur

Sanofi Pasteur is the most actively in-sourcing company in the sample. The five most actively technology sourcing companies are Sanofi Pasteur (45 alliances/41 in-sourcing), Merck & Co., Inc. (Merck) (21/19), GlaxoSmithKline plc (GSK) (22/14) , and MERIAL S.A. (Merial) (17/17). Together they are involved in 36% of all sampled vaccine alliances. All five firms are integrated pharmaceutical firms with *diverse* technological competences. All of them target various therapeutic areas for which preventive and/or therapeutic vaccines are under development. Roche, Sanofi Pasteur, Merck and GSK focus on human vaccines. Their therapeutic areas are partly but not completely overlapping. Merial is in the veterinary business. All five firms take a considerable share of their worldwide markets, which signals their capability to develop and commercialize vaccines.

We examine more closely Sanofi Pasteur because all its directed alliances on vaccines entered the sample. It had 45 alliances between 1994 and 2006 which entered the sample. This significantly influenced the analysis results which is based on a sample of 225 alliances.

Basic information Sanofi Pasteur is the human vaccines division of sanofi-aventis. Sanofi Pasteur is an integrated pharmaceutical business with diverse competences in vaccines research. It covers the whole value chain from research and development from production to commercialization. To date Sanofi Pasteur commercializes 21 vaccines all over the world with a slightly varying product portfolio in the different countries (Sanofi Pasteur, 2009). In Europe, its vaccines are marketed by Sanofi Pasteur MSD, a joint venture of the French Sanofi Pasteur S.A. and the American Merck & Co. Inc.. Sales worldwide in 2008 amounted to approximately 2.8 billion euros, implying a market share of around 20% on the global vaccine market (sanofi-aventis, 2008, p.39).[13]

Sanofi Pasteur currently has 28 vaccines under development (Sanofi Pasteur, 2009). Products under development are traditional prophylactic vaccines but also vaccines which open up new markets such as a prophylactic vaccine against HIV or a therapeutic vaccine against HPV (human papillomavirus) which might cause cancer. The new vaccines have been developed partly in-house, external or in joint partnerships.

[13]The business originates from Pasteur Mérieux Connaught, the vaccines division of the Rhône-Poulenc group. The subsequent mergers of Rhône-Poulenc with Hoechst AG to form Aventis in 1999 and Aventis with sanofi-synthélabo to form sanofi-aventis in 2004 led to several name changes of the respective vaccine businesses. Consistent with these name changes, all alliances conducted by Pasteur Mérieux Connaught, Aventis Pasteur and Sanofi Pasteur have been joined to build the alliance Portfolio presented here under the heading of Sanofi Pasteur. In Europe, Sanofi Pasteur markets its vaccines via Sanofi Pasteur MSD, which is a joint venture of the French Sanofi Pasteur S.A. and the American Merck & Co., Inc.. Pasteur MSD has been originally founded in 1994 as Pasteur Mérieux MSD; a joint venture of Merck & Co. Inc. and Pasteur Mérieux Connaught, a subsidiary of Rhône-Poulenc. Each party contributed its European vaccine business. The subsequent mergers of Rhône-Poulenc with Hoechst to form Aventis in 1999 and Aventis with sanofi-synthélabo to form sanofi-aventis in 2004 led to name changes of the European vaccine joint venture paralleling the name changes of the vaccines business but with 'MSD' appended. All of the alliances discussed are of the subsidiary of sanofi-aventis and not the joint venture with Merck.

Acquisition of external technologies and products have been via alliances (including licenses) as well as acquisitions.[14]

Alliances Table 5.5 summarizes the alliances of Sanofi Pasteur which entered the sample. Between 1994 and 2006, Sanofi Pasteur had 51 alliances with partners of various technological specialization (see first four columns of table 5.5).[15] In most of the alliances, Sanofi Pasteur in-sources technology, i.e. it acquires property rights on the (resulting) technology of the alliance (see column 'Techn. Flow' of table 5.5). Alliances include joint research, extramural research as well as pure licensing agreements. Examples in table 5.5 are alliances with ID 1, 40, and 47 respectively. This means that Sanofi Pasteur does active research in a broad range of projects jointly with collaborators as well as in isolation. Therefore, the business is likely to have the broad knowledge base which is necessary to act as system integrator as emphasized by Brusoni et al. (2001).

Indeed, Sanofi Pasteur in-sources vaccine components besides transversal technologies and vaccines. In some alliances, Sanofi Pasteur accesses vaccine components to develop vaccines against currently untreated diseases. For example in 2002, the business licensed two cancer related antigens from Epimmune Inc. (alliance ID 46 in table 5.5). Other vaccine components have been in-sourced in order to enhance or to extend the indication of already marketed vaccines. Here, one example would be the alliance with Emergent BioSolutions Inc. in 2004, where the alliance partner provides an antigen in order to extend the indication of Sanofi Pasteur's Meningitis vaccine (alliance ID 50 in table 5.5). Finally, we observe that in-sourced vaccine components are introduced into several vaccines. The first alliance (ID 1) provides a good example for this practice. In 1994 the business (at that time named Pasteur Merieux Connaught) licensed naked DNA vaccine technology from Vical Inc.. Both firms agreed that Sanofi Pasteur has the exclusive right to use this technology for six different vaccines.[16] Note that according to Ulrich (1995), using the same component in several products is one of the advantages of a modular architecture (see section 5.2.3). Furthermore, we observe that Sanofi Pasteur enhances existing product lines such as its flu vaccines and vaccines against children's diseases; the second advantage noted by Ulrich (1995). These benefits of modularity increase with the number of products. Therefore, the case of Sanofi Pasteur shows that firms with a large vaccine portfolio potentially profit more

[14] For example, in September 2008, Sanofi Pasteur acquired its former collaborator Acambis Plc (Acambis). Besides three joint development projects with Sanofi Pasteur, Acambis had two further vaccines under development. All the projects of Acambis have been based on Acambis' proprietary technology ChimeriVax for recombinant vaccines. Thus, Sanofi Pasteur acquired at least five products in development and one generic technology (Sanofi Pasteur, 2008).

[15] Six alliances of Sanofi Pasteur did not enter the sample because they are with non-profit institutions.

[16] These are vaccines against cytomegalovirus (CMV), respiratory syncytial virus (RSV), Lyme disease, Helicobacter pylori, malaria, and herpes zoster

from the modular architecture.

Finally, a vertical division of work between the business and its partners is prevalent. Partners mostly deliver research results and early stage development projects which are carried further by Sanofi Pasteur towards commercialization. This observation strengthens the argument in the literature section, that a vertical division of labor between biotechnology firms and pharmaceutical firms exists due to heterogeneity of resources.

Summary The literature discussion put forward two arguments for why integrated pharmaceutical firms are likely to in-source technology from all other firm types. The first argument is that the firm's endowment with technological, organizational and financial resources implies a vertical division of labor between integrated pharmaceutical firms and specialized biotechnology firms. Indeed, Sanofi Pasteur has strong capabilities in development and commercialization, which it leverages in practically all its alliances. The second argument is that integrated pharmaceutical firms are likely to act as an integrator of individual components because they have the necessary knowledge for integration and profit from integration. Also this is true for Sanofi Pasteur. Own research, alliances, and acquisitions seem to give the business the necessary architectural and component knowledge. Furthermore, benefits from the modular vaccine architecture seem to be especially high. Sanofi Pasteur's large vaccine portfolio allows for in-sourcing individual components in order to enhance one product or simultaneously several products of its portfolio. Furthermore many research projects on untreated diseases are leveraged by in-sourcing external technology.

Table 5.5: *Alliances of Sanofi Pasteur*

ID	Year	Partner name	Partner techn. [a]	Flow	Technology	Product [b]	Division of work[c]	
							Partner	Sanofi Pasteur
1	1994	Vical	Vector	Source	Vector	Six naked DNA V	R	R/D/Prod/Com
2	1994	Antex Biologics	Antigen	Source	n.a.	Otitis Media V	n.a.	n.a.
3	1994	Avant Immuno.	Vector	Source	Vec./Adj.	Flu/Lyme V	-	D/Prod/Com
4	1995	Cornell University		Bi-dir.	n.a.	Tuberculosis V	n.a.	n.a.
5	1995	Id Biomedical	Ant./Adj./Oth.	n.a.	n.a.	Tuberculosis V		n.a.
6	1995	Emisphere Tech.	Oth.	Source	Other	Delivery for Flu V	R	D/Prod/Com
7	1995	Vaxcel	Adj./Oth.	Source	Adjuvant	Flu V	n.a.	n.a.
8	1995	Avant Immuno.	Vector	Source	Vec./Adj.	Delivery for Vs	R	D/Prod/Com
9	1995	Nventa Biopharma.	Adjuvant	n.a.	n.a.	n.a.	n.a.	n.a.
10	1995	Id Biomedical	Ant./Adj./Oth.	n.a.	n.a.	Tuberculosis V	n.a.	n.a.
11	1995	Protein Sciences	Cell	Source	Antigen	Flu V	-	D/Prod/Com
12	1995	Oravax	Antigen	Bi-dir.	Ant./V	H. Pylori V	D (JV)	D (JV), Com
13	1995	North American V.	Antigen	Source	Vaccine	Meningitis B V	D	D, Fin.
14	1995	Rgene Therapeutics	Vector	n.a.	n.a.	n.a.	n.a.	n.a.
15	1996	Human Genome Sc.	Diagn.	Source	Other	Genome of H. Pylori	R/D (JV)	R/D (JV)
16	1996	Iscotec	Adjuvant	n.a.	Adjuvant	n.a.	n.a.	n.a.
17	1996	Corixa	Adjuvant	Source	Adjuvant	Several V	–	R/D/Prod/Com
18	1997	Imclone Systems	Other	supply	Vaccine	HIV V	D	Prod/Com
19	1997	Rhone-Poulenc Rorer	Diverse	n.a.	n.a.	Gene therapy	n.a.	n.a.
20	1998	Therion Biologics	Ant./Adj.	Source	Vaccine	Cancer V	R/D	Fin
21	1998	Vaxgen	Ant./Cell	Source	V (boost)	HIV V	D	D
22	1998	Zycos	Ant./Vec.	Source	Antigens	Cancer V	–	R/D/Prod/Com
23	1998	Btg	Diverse	Source	Vector	Unkn. V	–	R/D
24	1998	Oravax	Antigen	Source	Ant./Vec.	Dengue V	R/D	Fin/Com
25	1998	Lion Bioscience	Diagn.	Source	Diagnostics	Several V		R
26	1998	Medimmune	Ant./Oth.	Source	Antigen	Enhanced Lyme V	–	R/D
27	1999	Acambis	Ant./Cell	Source	Ant./Vec.	West-Nile V	D	Fin/Com
28	1999	Visionary Med. Prod.	Other	Source	Other	Delivery for Flu V	Prod.	D
29	1999	Rhein Biotech Ag	Adj./Cell	Source	Other	Hepatitis B Antibody		Prod
30	1999	Zycos	Ant./Vec.	Source	Antigens	Cancer V	n.a.	R/D/Com
31	1999	Dyax	Diagn.	Source	Antigen	Unkn. V	R	R/D/Com
32	1999	Chiron	Ant./Adj./Cell	Source	Vaccine	CMV V	–	D/Com

Alliances of Sanofi Pasteur (continued)

ID	Year	Partner name	Partner techn. [a]	Flow	Technology	Product [b]	Division of work[c]	
							Partner	Sanofi Pasteur
33	2000	Eos Biotechnology	Diagn.	Source	Antigen	Cancer V	R	R/D
34	2000	Chiron	Ant./Adj./Cell	Source	Vaccine	Menj./Fluad V	Prod	Com
35	2000	Active Biotech	Ant./Adj.	Source	Vaccine	Cholera V	Prod	Com
36	2001	Fibrogen	Other	Source	Other	Stabilizer for live V	D	D
37	2001	Vivalis	Cell	Source	Cell	Several V	–	Prod
38	2001	Sbl Vaccin Ab	n.a.	Source	Cell	Unkn. Vaccine	Prod	Com
39	2001	Transgene	Ant./Vec.	Bi-dir.	Vector	n.a.	n.a.	n.a.
40	2001	Maxygen	Ant./Diagn.	Source	Ant./Vec.	Unkn. V	R/D	Fin/Com
41	2002	Epimmune	Antigen	Source	Antigen	Cancer V	–	R/D
42	2002	Nautilus Biotech	Adj./Oth.	Source	Cell	Unkn. V	R	Fin
43	2003	CruCell / Berna Rhein	Vec./Cell/Diagn.	Source	Cell	Unkn. V	n.a.	D/Prod
44	2003	CruCell / Berna Rhein	Vec./Cell/Diagn.	Source	Cell	Flu V	–	Prod
45	2004	Provalis	Other	Source	Vaccine	S. Pneum. V	R	D
46	2005	Agensys	Ant./Oth.	Source	Target	Cancer V	–	R/D/Prod/Com
47	2005	Eisai	n.a.	Source	Adjuvant	Unkn. V	–	R/D
48	2005	Becton Dickinson	Diagn./Oth.	Source	Other	Delivery unkn. V	R	D
49	2006	Nabi	Ant./Oth.	Source	Other	Rabies Antibody	Prod	D/Com
50	2006	Emergent Biosolutions	Ant./Oth.	Source	Antigen	Meningitis B V	D	D/Com/Fin
51	2006	Medigene	Vec./Oth.	Source	Diagnostics	T-Cell Diagn.	D	Fin

[a] Ant. - Antigen, Vec. - Vector, Adj. - Adjuvant, Diagn. - Diagnostics, Oth. - Others V. - Vaccine(s), n.a. - not available, unkn. - unknown
[b] Menj. - Menjugate, CMV - Cytomegalovirus, S. Pneum. - Streptococcus pneumoniae
[c] R - Research, D - Development, Prod - Production, Com - Commercialization, Fin - Financing, JV - Joint Venture,
- - no contribution besides technology licensing

5.4.2 The Case of Crucell

The technology flow among specialized biotechnology firms does not show the clear pattern which has been implied by the literature discussion. One reason might be that the theoretical argumentation was wrong or incomplete. Another reason might be that simplifying assumptions in the empirical analysis yield misleading results. The following case on Crucell N.V. (in the following Crucell or the company) serves to clarify these issues. The company has been chosen because it is a multi-technology firm which grew from a specialized biotechnology firm to an integrated pharmaceutical firm. Thus, the case allows us to review the argumentation of the literature discussion as well as simplifying assumptions of the empirical analysis.

Incorporation Crucell is a limited liability company incorporated in The Netherlands. Crucell has been incorporated in the year 2000 as the holding company of Crucell Holland B.V., which resulted from the acquisition of U-BiSys B.V. (U-BiSys) by IntroGene B.V. (IntroGene). In the same year, the company had its initial public offering (IPO) on Euronext and NASDAQ. After the merger, total assets reached 200 million Euros. An income of about 7 million Euros from licensing revenues (6 million Euros) and contract research and governmant grants (1 million Euros) faced expences from ordinary activities of about 15 million Euros for research and overhead (each about 7.5 million Euros) (Crucell N.V., 2001, p.50). End of December 2000, Crucell had 110 full-time employees, 85 of whom were engaged in, or directly supported, research and development activities, and 25 were in administrative and business development positions (Crucell N.V., 2002, p.46). Thus, the merger generated a very large biotechnology firm. The number of employees as well as R&D spending double those of a typical biotechnology firm having an age between 10 and 15 years (EuropaBio, 2005, p.21).

Technological and business development For its further development, Crucell built on the technologies developed by U-BiSys and IntroGene. IntroGene has been founded in 1993 by the two scientists Jack Roth and Dinko (Domenico) Valerio. At this time, Dinko Valerio held a professorship in Gene Therapy at Leiden University in The Netherlands and IntroGene collaborated with Leiden University to develop its human cell line technology, commercialized under the registered trademark Per.C6. The cell line is based on a human fetal cell which has been genetically modified so that it can replicate itself indefinitely. Such a cell line allows for controlled replication of viruses or production of proteins. This opens up production of and research on i) fully-human antibodies and other therapeutic proteins, ii) classical and recombinant vaccines, iii) gene therapy[17] and iv) functional genomics[18] (Crucell N.V., 2002, p.16). For use in combination with its cell line technology, IntroGene developed the proprietary adenoviral vector AdVac. The adenoviral vector may be used as carrier for gene-related vaccines and can be produced within the cell line. Based on its proprietary technologies, IntroGene is categorized as specialized in *cell* and *vector* technology.

Similar to IntroGene, U-BiSys has been founded by two scientists. In 1996, when IntroGene was founded, both scientists held a position at the University of Utrecht, The Netherlands. U-BiSys developed a phage antibody-display library called MAbstract, which became the third core technology of Crucell. The phage antibody-display library is a high-throughput screening technology used for discovery of antibodies binding to new or known drug targets. In addition, U-BiSys had strong competences in genetic engineering related to the creation of fully-human antibodies (Crucell N.V., 2002, p.17). Both the phage-display library and the genetic engineering competence are general purpose technologies which fall in the category *drug discovery / diagnostics*. Thus, Crucell started with three core technologies: *cell*, *drug discovery / diagnostics* and *vector*.

The overall business strategy of the newly founded company has been to commercialize its technology via i) licensing and contract research and ii) development of own products in-house and in collaboration (Crucell N.V., 2001, p.22).[19] From its predecessors, Crucell inherited a product pipeline with eight fully human antibody products and one flu-vaccine in pre-clinical stages (Crucell N.V., 2001, p.22). The firm developed the flu-vaccine mainly because it perceived that Per.C6 has comparative advantages in production and not because it found a novel or superior antigen (Crucell N.V., 2002, p.22). In the year 2003, Crucell agreed with Aventis Pasteur S.A. on joint collaboration of the flu-vaccine. According to the agreement, Aventis Pasteur S.A. did further research, development, manufacturing and commercialization using the Per.C6 cell line (Crucell N.V., 2004, p.27).

In the same year, Crucell started vaccine projects targeting West Nile, Ebola and Malaria. The West Nile vaccine has been developed entirely in-house. This vaccine

[17] "Gene therapy seeks to treat certain diseases through the transfer of a therapeutic gene into the cells of the patient to replace absent or defective genes or to stimulate a target cell into producing a therapeutic protein. Per.C6 can be used to produce adenoviral vectors carrying therapeutic genes, which can be used to treat patients by delivering the therapeutic gene into their cells. Adenoviruses can be modified for use as a vector - a gene delivery mechanism by replacing naturally existing genes in the virus with specific genes for therapeutic purposes." (Crucell N.V., 2002, p.16) Gene therapy is sometimes used interchangeably with (prophylactic or therapeutic) DNA vaccines as both let foreign DNA be expressed by human cells in vivo (Liu et al., 2004, p.14567).

[18] "Our Per.C6 technology can be used to produce libraries of adenoviruses into which genes to be studied have been inserted. The resulting adenoviral vectors can then be put into cells and the effects of their expression analyzed to determine the function of genes in a disease process." (Crucell N.V., 2002, p.16).

[19] A third route to commercialization has been to set up Galapagos N.V., a joint venture with the Belgian biotechnology firm Tibotec B.V.B.A., for research in in the field of functional genomics.

follows the classical approach by growing the West Nile Virus in the cell line and inactivating it (see patent De Vocht et al., 2006). Within such a process, research on antigen seems not to be crucial. The other two vaccines have been joint development projects. For development of the Ebola vaccine, Crucell collaborated with the U.S. based Vaccine Research Center of the National Institute of Allergy and Infectious Diseases (NIAID), one of the institutes of the National Institutes of Health (NIH). In this project NIAID supplied genes encoding Ebola antigens to Crucell. Crucell introduced these genes into its vector AdVac, which in turn has been produced with the cell line Per.C6 (press release). For development of the Malaria vaccine, Crucell collaborated with the U.S. Walter Reed Army Institute of Research (WRAIR) and GlaxoSmithKline Biologicals (GSK) (Crucell N.V., 2004, p.27ff). The DNA fragment of the Malaria antigen has been known beforehand from public research (Bruna-Romero et al., 2001). The novelty of the developed vaccine is to express it in the carrier provided by Crucell (see patent Maria Pau, 2008). One more vaccine project followed in the year 2004. Crucell entered a new collaboration with the Aeras Global TB Vaccine Foundation on the development of a tuberculosis vaccine. The aim was to improve an existing vaccine/antigen through production in Per.C6 and formulation within the AdVac vector (Crucell N.V., 2005, p.40). In the same year, Crucell acquired ChromaGenics B.V. and its proprietary STAR technology. This technology improves the production of recombinant antibodies and therapeutic proteins in mammalian cells and, hence, in the Per.C6 cell line. Thus, the STAR technology rather strengthened than diversified Crucell's portfolio of technologies.

The strategy of own product development seemed to force diversification into complementary business activities. In 2006, Crucell acquired the Swiss based Berna Biotech AG to become a fully integrated pharmaceutical firm. This acquisition gave Crucell access to 900 additional employees, various projects including novel technologies, several marketed products and marketing and distributional capability in Europe and Korea (Crucell N.V., 2007, p.21,28). To date it develops, produces and markets drugs in-house as well as in cooperation with many partners. As of the end of 2008, Crucell marketed 8 paediatric, travel and endemic vaccines all over the world. It has six further vaccines in various stages of development (against yellow fever, influenza, tuberculosis, malaria, ebola and marburg and HIV) and two antibody products (against rabies and influenza), mostly developed together with a strategic partner (Crucell N.V., 2009, p.19). As of end of 2008, Crucell employed in total 1,100 people, generated total revenues of 270 million Euros (with product sales 230 million Euros, license fees 30 million Euros, services 10 million Euros), 130 million Euros operating expenses (research 70 million Euros, overhead 65 million Euros) and 145 million Euros total cost of goods sold (Crucell N.V., 2009, p.44,127). Thus, with the acquisition of Berna Biotech in 2008, Crucell became an integrated pharmaceutical firm with *diverse* competences.

The technological development of Crucell may be summarized as follows: in the year 2000, Crucell started with three distinct and complementary technologies in the fields *cell*, *drug discovery / diagnostics* and *vector*. In the following 6 years, all internal projects aimed to further develop these technologies or to apply these technologies for proprietary drugs. In particular, the increasing number of drug development projects did not force technological diversification. Crucell in-sourced the antigen DNA fragments and transfected them into its proprietary vector. This exemplifies how modularity in vaccines allows for division of research.[20]

For the assessment of the empirical analysis it is noticeable that the core competences of Crucell (and its predecessors) did not change due to organic growth. Major changes in the technological specialization are due to external growth, i.e. when Crucell is founded and when it acquired Berna Biotech. In the empirical analysis, technological specialization of the firm is assumed to be stable in general but changes in technological specialization due to mergers and acquisitions are taken into account. With respect to Crucell this approach seems to be justified.

Licensing Already prior to the incorporation of Crucell, in the years 1998 and 1999, IntroGene commercialized its Per.C6 technology through non-exclusive licensing to biotechnology and pharmaceutical firms. Agreements targeted mainly development of gene therapy products but also vaccines.[21] Crucell successfully continued out-licensing its cell technology after the merger. At the end of 2008, Crucell counted 70 licensing agreements or partnerships for developing vaccines (14), proteins (39), gene therapy (7), functional genomics (1) and manufacturing agreements (9). Out of these 70 agreements, 59 build primarily on the cell technology Per.C6 (Crucell N.V., 2009, pp.185-187). The second most out-licensed technology is the cell technology STAR with 8 licenses. The other technologies, AdVac (vector) and MAbstract (diagnostics / drug discovery), have little significance in the overall licensing and partnering activity.

The alliance activity observed in the sample follows the same pattern (see table 5.6). In the large majority of alliances, Crucell licenses its Per.C6 cell technology. The cell line has been used for research as well as production for multiple indications. Other technologies are of minor importance for alliance formation. Because Crucell was a firm with multiple specializations (including vector, cell, and diagnostics) but most alliances focus on its cell technology, equating technological specialization and alliance

[20] Note that the literature discussion did not suggest that vector firms integrate vaccine components. The argument was that vector firms have a weak bargaining-power vis-a-vis antigen firms because vector technology is easier to substitute. However, the partners which provided the antigen to Crucell have been non-profit research organizations. Therefore, the case of Crucell is not contrary to the bargaining argument. Nevertheless, the case shows that non-profit research institutions and further actors of the pharmaceutical field heavily influence economic and technological development of firms in the industry.

[21] Firms involved have been Genzyme Corporation, Schering AG, Merck & Co. Inc., Novartis, Aventis Pharmaceutical Products Inc., Pfizer/Warner-Lambert, Cobra Therapeutics Ltd. and GlaxoSmithKline plc.

content results in a large bias in the case of Crucell. Simply splitting each alliance over its fields of specialization overemphasizes Crucell's role as *vector* and *drug discovery / diagnostics* specialist and underestimates its role as *cell* specialist in the industry.

Summary The empirical analysis made two major simplifying assumptions. Firstly, it has been assumed that the firm's technological specialization remains the same throughout the considered time period. Secondly, because information on the technological content of alliances was not available, each alliance of a multi-technology firm counted to equal parts for each of the firm's technologies. The first assumption is not put into question by the case. Despite its growth, Crucell's technological specialization remained remarkably stable. The second assumption, however, might have prevented the emergence of the expected pattern of technology flow. Whereas Crucell is specialized in cell, diagnostics and vector technology, it out-licensed predominantly it's cell technology.

Based on public information, we describe the economic and technological development of the company. Crucell's strategy was to commercialize early it's transversal technology by out-licensing and, at the same time, to develop own products. This strategy has not been considered in the literature section for two reasons. Firstly, there was the (implicit) assumption that technological specialization determines the strategy of the firm. Secondly, non-profit actors of the pharmaceutical field, specifically non-profit research organizations, have been excluded from this study. The reason was that incentives of for-profit and non-profit organizations are likely to differ. However, Crucell had relevant generic competences and a large initial success in out-licensing its transversal technology. This enabled the company to in-source antigens from non-profit organizations, develop its own products and even acquire the complementary resources needed for distribution and marketing. Thus, the case shows that non-profit research organizations are a relevant tier in the pattern of technology flow. In addition, the firm's technological specialization does not seem to predetermine its strategy.

5.5 Discussion and Conclusion

Modular product architectures facilitate the division of innovative labor across firms. Once a modular architecture is specified, firms may simultaneously and independently develop individual components which adhere to the specification. Moreover, in case the architecture becomes an industry standard, firms become autonomous in that no a priori coordination is required between the firm which develops a product component and the firm which integrates this component. Although these arguments have been previously invoked with respect to engineering products, they seem to capture also the situation of industrial research on vaccines.

Most importantly, we observe that biotechnology firms simultaneously and au-

Table 5.6: *Alliances of Crucell with sample firms*

Year	Partner name	Partner techn. [a]	Techn. flow	Technology	Objective	Alliance type [b]
2000	Merck	Diverse	Supply	Per.C6 cell	HIV vaccine development	License, Option
2002	Innogenetics	Ant., Diagn.	Supply	Per.C6 cell	Antibody production	License
2002	Rhein Biotech Ag	Adj., Cell	Supply	Per.C6 cell	Japanese Encephalitis vaccine develop.	License
2002	Medimmune	Ant., Other	Supply	Per.C6 cell	Influenza vaccine develop./prod.	License
2003	Aventis Pasteur	Diverse	Supply	Per.C6 cell	Unknown vaccine develop. and prod.	License
2003	Merck	Diverse	Supply	Per.C6 cell	Antibody production	License
2003	Novavax	Ant., Adj.	Supply	Per.C6 cell	Unknown vaccine develop./prod.	License, Prod., Develop.
2003	Glaxosmithkline	Diverse	Bi-directed	AdVac vector	Res. to combine two Malaria vaccines	Research, Collaboration
2003	Aventis Pasteur	Diverse	Supply	Per.C6 cell	Influenza vaccine production	License, Res., Develop.
2004	Chiron	Ant., Adj., Cell	Supply	Per.C6 cell	Antibody production	License
2004	Glaxosmithkline	Diverse	Supply	Per.C6 cell	Antibody research and development	License
2004	Merial	Diverse	Supply	Per.C6 cell	Foot-and-Mouth vaccine res./develop.	License
2004	Chiron	Ant., Adj., Cell	Supply	Per.C6 cell	Alphavirus vaccine development	License
2005	Medarex	Other	Supply	Star cell	Antibody production	Develop., Prod.
2005	Chiron	Ant., Adj., Cell	Supply	Per.C6 cell	Protein production	License
2005	Merial	Diverse	Supply	Per.C6 cell	Veterinary gene-therapy research	License, Option
2006	Novartis	Diverse	Supply	Star cell	Protein production	License
2006	Merck	Diverse	Bi-directed	Per.C6 cell	Vaccine research and production	Cross-License

[a] Ant. - Antigen, Adj. - Adjuvant, Diagn. - Diagnostics
[b] Res. - Research, Develop. - Development, Prod. - Production

tonomously do research on components of a vaccine. The explanation is that problem decomposition in the life sciences shifted the product architecture of vaccines from an integrated to a nearly modular product architecture. More specifically, scientific advance led to a specialization in research on vaccines and the common perception that a vaccine provides essentially three functions which might be provided by three different components. The one-to-one mapping of functions onto components allows specialized firms to do simultaneously research on components. Moreover, similar to an industry standard, the actors in the industry have a common perception of vaccines as nearly modular products. Therefore, firms can do research not only simultaneously but also autonomously, without a priori coordination.

That a division of research on vaccines among firms takes place has been observed within the MiDeV project (Bonah et al., 2007). The main question of this chapter is which pattern of technology flow is associated with the division of labor. Specialization of research on vaccine components necessitates the transfer of components across firm boundaries and integration of components by some firm(s). Technology flow is going to be directed towards the firm which integrates the components.

Several theoretical arguments support the idea that integrated pharmaceutical firms are likely to act as integrators. They have the necessary broad knowledge base (Brusoni et al., 2001), complementary resources for commercialization (Teece, 1986) and are able to exploit advantages of modular product design due to their large vaccine portfolios (Ulrich, 1995). Other arguments led us to expect that biotechnology firms specialized in *antigen* take over the role of the integrator. Firstly, new biotechnology firms might be more efficient in integration due to higher technological competence in the new research regime. Secondly, biotechnology firms might appropriate a higher return from their efforts the more developed the product is due to increasing bargaining power vis-a-vis pharmaceutical firms. Thirdly, firms specialized in *antigen* are likely to have a stronger bargaining power vis-a-vis firms specialized in the other two components because antigens are least substitutable (Jacobides et al., 2006).

In the sample of directed technology transfers among French vaccine firms and their collaborators, pharmaceutical firms in-source the lion share of technology. The empirical analysis confirms that integrated pharmaceutical firms in-source technology from biotechnology firms of all specializations at a high rate. Investigation of the alliances of Sanofi Pasteur suggest that the theoretical arguments with respect to pharmaceutical firms hold. Most importantly, Sanofi Pasteur takes advantage of the modular product architecture in its product life cycle management. In particular, an in-sourced component may be introduced in several product lines and products are continuously improved by adding or replacing components.

The empirical analysis on the pattern of technology flow among biotechnology firms is less clear. Partly this is because technology flow among biotechnology firms is rather weak; most of the technology is in-sourced by pharmaceutical firms. Another reason is that some firms are specialized in more than one field. Given two firms with multiple technological specialization, theoretical arguments suggested a symbiotic interdependence for one combination of technologies but not for the other.

Nevertheless, in accord with the arguments on bargaining power among component firms (Jacobides et al., 2006), permutation tests show that technology transfer between adjuvant and vector firms is weak. Also, there is a high propensity of *antigen* firms to collaborate with each other. Investigation of these alliances shows that this is caused partly by integration activities of these firms, which has been expected from the theoretical discussion. Furthermore, the direction of technology flow from transversal technology firms to co-specialized component firms is statistically confirmed for some firm type combinations. Finally, the data does not show that firms tend to collaborate across scientific domains rather than within scientific domains (Bureth et al., 2007). However, the empirical analysis also does not show the opposite.

The empirical analysis is complemented by a more detailed account of the biotechnology firm Crucell. Crucell's commercial success in licensing its transversal technology opened the route for product development and acquisition of complementary resources for marketing. For its strategy, collaboration with non-profit research organizations has been important because they provided the strategic vaccine component *antigen*. The case does not put into question the theoretical arguments on the bargaining power among biotechnology firms. However, the case yields the important insight that the technological specialization does not determine the strategy of the firm because hierarchical relationships among firms resulting from technological specialization may be circumvented by partnering with non-profit research organizations.

APPENDIX D

Sample Statistics

This section provides descriptive statistics on the sample used for the empirical analysis. Table D.1 displays which categories have been ascribed to firms in the sample. Note that some firms have multiple specializations. For example there are 14 firms which are specialized in *antigen* and *adjuvant*.

Table D.1: *Categorization of sample firms* [a]

	Diverse	Antigen	Adjuvant	Vector	Diagnostic	Cell	Other Drug	n.a.
Diverse	20.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Antigen	0.0	38.0	14.0	12.0	10.0	6.0	0.0	0.0
Adjuvant	0.0	0.0	26.0	0.0	2.0	4.0	0.0	0.0
Vector	0.0	0.0	0.0	29.0	2.0	10.0	0.0	0.0
Diagnostic	0.0	0.0	0.0	0.0	28.0	2.0	0.0	0.0
Cell	0.0	0.0	0.0	0.0	0.0	15.0	0.0	0.0
Other Drug	0.0	0.0	0.0	0.0	0.0	0.0	21.0	0.0
n.a.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.0

[a] Some firms have multiple specializations. For example there are 14 firms which are specialized in antigen and adjuvant at the same time.

Table D.2 indicates the involvement of firm types in acquisitions among firms in the population. Acquisitions among firms with multiple specialization weight for each firm type combination equally such that they sum to one. Therefore table D.2 contains rational numbers. The table gives, from the left to the right, which firm types have been acquired by which other firm types. For example, a share of 1.6 *adjuvant* firms has been acquired by *diverse* firms (see table D.2). The table reveals that most firms have been absorbed by *diverse* firms or by firms of similar type. This pattern fits well the interdependence among firms depicted in the earlier sections.

Table D.2: *Acquisitions by firm categories (weighted)*

	Diverse	Antigen	Adjuvant	Vector	Diagnostic	Cell	Other	$\sum$
Diverse	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Antigen	0.5	1.0	0.5	0.0	0.0	0.5	0.0	2.5
Adjuvant	1.5	0.5	1.1	0.6	0.1	0.1	0.0	4.0
Vector	0.0	0.5	0.0	0.5	0.0	0.0	0.0	1.0
Diagnostic	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Cell	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.5
Other	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
$\sum$	2.0	2.0	1.8	1.2	0.2	0.8	1.0	9.0

The last table, table D.3, gives some basic statistics on the dynamics of the population and the alliances for the years 1994 until 2006. The population of firms increases from 79 firms in the year 1994 up to 131 firms in the year 2006 (see 'nb. firms' in table D.3). The number of firms with competences in *antigen*, *adjuvant* and *cell* first increase, reach a maximum in the early years of this century and then decrease again, where exits are most often due to acquisitions.

Table D.3: Population and alliance formation over years (percentage in brackets).

Year	1994	1995	1996	1997	1998	1999	2000	2001
Nb. firms	79 (100)	89 (100)	91 (100)	101 (100)	107 (100)	118 (100)	122 (100)	129 (100)
Diverse	15 (19)	15 (16.9)	15 (16.5)	16 (15.8)	17 (15.9)	17 (14.4)	18 (14.8)	18 (14)
Antigen	20 (25.3)	23 (25.8)	23 (25.3)	26 (25.7)	29 (27.1)	31 (26.3)	31 (25.4)	33 (25.6)
Adjuvant	14 (17.7)	14 (15.7)	15 (16.5)	15 (14.9)	16 (15)	21 (17.8)	22 (18)	22 (17.1)
Vector	10 (12.7)	14 (15.7)	15 (16.5)	16 (15.8)	17 (15.9)	19 (16.1)	20 (16.4)	23 (17.8)
Diagnostic	9 (11.4)	12 (13.5)	12 (13.2)	16 (15.8)	17 (15.9)	19 (16.1)	20 (16.4)	20 (15.5)
Cell	8 (10.1)	8 (9)	9 (9.9)	9 (8.9)	10 (9.3)	12 (10.2)	13 (10.7)	14 (10.9)
Other	17 (21.5)	19 (21.3)	19 (20.9)	21 (20.8)	22 (20.6)	24 (20.3)	25 (20.5)	27 (20.9)
Nb. alliances	9 (100)	13 (100)	11 (100)	19 (100)	25 (100)	23 (100)	29 (100)	30 (100)
Equity/ownership	2 (22.2)	2 (15.4)	0 (0)	3 (15.8)	5 (20)	3 (13)	2 (6.9)	2 (6.7)
Vaccine	7 (77.8)	11 (84.6)	9 (81.8)	14 (73.7)	21 (84)	21 (91.3)	20 (69)	23 (76.7)
Directed vaccine	7 (77.8)	4 (30.8)	5 (45.5)	11 (57.9)	20 (80)	17 (73.9)	19 (65.5)	21 (70)

Year	2002	2003	2004	2005	2006	sum	avg
Nb. firms	134 (100)	131 (100)	135 (100)	133 (100)	131 (100)	1500 (100)	115 (100)
Diverse	18 (13.4)	18 (13.7)	18 (13.3)	18 (13.5)	18 (13.7)	221 (14.7)	17 (14.7)
Antigen	34 (25.4)	32 (24.4)	34 (25.2)	31 (23.3)	30 (22.9)	377 (25.1)	29 (25.1)
Adjuvant	21 (15.7)	20 (15.3)	20 (14.8)	19 (14.3)	18 (13.7)	237 (15.8)	18 (15.8)
Vector	23 (17.2)	23 (17.6)	23 (17)	26 (19.5)	26 (19.8)	255 (17)	20 (17)
Diagnostic	23 (17.2)	22 (16.8)	23 (17)	23 (17.3)	23 (17.6)	239 (15.9)	18 (15.9)
Cell	14 (10.4)	14 (10.7)	15 (11.1)	14 (10.5)	13 (9.9)	153 (10.2)	12 (10.2)
Other	28 (20.9)	28 (21.4)	28 (20.7)	28 (21.1)	28 (21.4)	314 (20.9)	24 (20.9)
Nb. alliances	30 (100)	27 (100)	27 (100)	31 (100)	30 (100)	304 (100)	23 (100)
Equity/ownership	2 (6.7)	0 (0)	0 (0)	2 (6.5)	3 (10)	26 (8.6)	2 (8.6)
Vaccine	27 (90)	21 (77.8)	23 (85.2)	27 (87.1)	23 (76.7)	247 (81.2)	19 (81.2)
Directed vaccine	28 (93.3)	20 (74.1)	25 (92.6)	27 (87.1)	21 (70)	225 (74)	17 (74)

CHAPTER 6

Conclusion

The dramatic increase in alliances among firms has led to a large, and growing literature attempting to understand its causes and effects. We see this in sociology, economics, business and management studies among other fields. One over-riding concern has been to explain the formation of bilateral alliances, and to understand why particular pairs of firms partner, while others do not. One of the common explanatory factors has been social capital, which tends to be linked, in the literature, to past (and present) industry network structures. There is, thus, a two-way link between alliances and networks: on the one hand bilateral alliances are the basic building blocks of industry-wide networks; on the other, the structure of existing networks is thought to influence future alliance behavior. Part of the goal of this thesis is to understand better that interaction.

If the alliance behavior of firms would follow a deterministic model of which all parameters were known to us, then the formation of the alliance network would be completely given as well. In fact, though, our knowledge on the firm's alliance behavior is very limited and, a priori, it is not clear to what extent this limited knowledge helps to explain the formation of higher-level network structures. Therefore, one aim of this thesis has been to better understand the alliance behavior of the firm and to clarify the extent to which this knowledge actually helps to explain the formation of networks.

The starting point of the thesis has been a theoretical model which shows how the technological endowment of firms may influence the network structure. The basic assumption of the model is that the profit for two firms from forming an alliance follows an inverse-U-shaped function of their technological distance. The micro-economic foundation of the assumption is the trade-off between absorptive capacity and novelty gain (Cohen and Levinthal, 1990; Nooteboom et al., 2007). For a beneficial alliance both would be preferred to be high. However, absorptive capacity responds negatively and novelty gain positively on an increase in technological distance. Therefore, the expected benefit of an alliance is likely to be maximal at some intermediate point of technological distance. The inverse-U-shaped benefit-distance effect has been empirically validated by Mowery et al. (1998) and Nooteboom et al. (2007). They found that two firms having an intermediate technological distance are most likely to join for research and development. The model is concerned with how the benefit-distance relationship between firm-pairs shapes the firm's ego-network and the global network structure.

The model assumes that firms are uniformly distributed in a bounded technological space. The inverse-U-shaped benefit-distance relationship implies that alliance formation is beneficial for firm-pairs within a certain distance range, the profitable distance range. All firm-pairs within the profitable distance range form an alliance. Therefore, given the positions of firms in technological space and the profitable range, the network is completely determined. We analyze how variations of the profitable distance range generate different networks.

While other models begin to generate real-world-like networks, the added value of our model is to shift the focus of the analysis from the global network structure to the firm's ego-network. The analysis demonstrates how the firm's position in network space becomes a function of the firm's position in technological space. The central result is that we observe two different regimes depending on the specification of the benefit distance range. If small (large) technological distances are profitable for alliance formation, then agents in the center (at the boundary) of technological space are more central in the network.

The model exemplifies a more general insight. Because firms are heterogeneous in their endowments, each firm faces a different set of potential alliance partners, both in size and in composition. The differences in the inducement of alliance formation are likely to be visible in the firm's ego-network as well as the global network structure. The theoretical model proposes that the technological endowment of firms together with how knowledge is profitably (re-)combined has this effect.

In chapter 3, the technological distance effect on network formation is tested empirically on a research network of the pharmaceutical industry. As a result of the biotechnology revolution, the knowledge space in the pharmaceutical industry has become fragmented. This means that firms have heterogeneous technological capabilities and frequently need to pool their technological knowledge in joint research alliances. In addition, patenting is frequent in this industry which facilitates the measurement of the technological knowledge of the firm. This makes the pharmaceutical industry a promising field to test the model.

The theoretical model is tested in three steps. First, the basic assumption of the model is validated by estimating the effect of technological distance on pairwise alliance formation. The estimates assign to each firm-pair the probability to realize an alliance. Then, in a monte carlo approach, the estimated probabilities are used to simulate networks which are used to get expected network statistics. In the second step, expected and observed statistics on the firms' ego-networks are compared. In the third step, we relate expected and observed statistics on the global network.

Simulation of networks based on estimated probabilities of link formation and subsequent comparison of observed and simulated network statistics has been originally proposed by Goodreau et al. (2007). In this thesis it is done for the first time, we think, for alliance networks. In addition, ego-networks are considered next to the global network structure.

The estimation results imply that the probability of alliance formation is an inverse-U-shaped function of technological distance. The optimal technological distance, where alliance formation is most likely, is estimated to be relatively short. However, the sensitivity analysis shows that different measures of technological distance yield different results. Besides overlap, we constructed two further measures, uncentered correlation and correlated revealed technological advantage. For correlated revealed technological advantage alliance formation is most likely for firms which are technologically close. The third measure of technological distance, uncentered correlation of the patent class vectors, is insignificant.

Thus, estimates of the distance-benefit effect vary with the distance measure. A possible interpretation is that different measures capture different aspects of technological distance. The technological space is complex and high-dimensional. Therefore it is likely that firms consider a great variety of technological aspects which influence their decision to form an alliance in different ways. Formalizing this decision process and measuring the technological fit of firms probably captures some aspects and neglects others. Which aspects are emphasized depends on how we measure technological fit. Therefore, we would not expect that different measures of technological distance yield the same results.

Using the overlap measure, alliance formation is most likely between firms at relatively short distance. The theoretical model implies that when alliance formation is beneficial for two firms having a short technological distance, firms which are central in technological space are going to be central in the network of alliances. Descriptive statistics show that this is the case in our sample.

The econometric analysis attests empirical relevance to the theoretical model. We show that taking into account the firm's technological position in a model of pairwise alliance formation helps to explain the firm's ego-network structure. Compared to the base line model which only includes firm size information, adding the size dimension of the firm's technological position, that is the size of the firm's patent portfolio, improves significantly predictions of the firm's degree centrality, closeness centrality, and clustering coefficient. Adding the structural dimension, firm-pair overlap in patent classes, further improves significantly predictions of the firm's degree centrality.

The econometric result hints at the importance of patent portfolio size on the firm's network position. This corresponds to findings of Ahuja (2000) who finds a positive effect of the firm's number of patents on its number of research alliances. Whereas Ahuja (2000) estimates this effect directly, we observe this effect as the outcome of a model of pairwise alliance formation.

Including the firm's technological characteristics in a model of pairwise alliance formation is not especially informative for the global network structure. The base model with only firm size generates networks with a degree distribution (distribution of number of alliances in the network) very close to the observed one. The base model does not fit well the distributions of the other network statistics. Taking into account the firm's technological position does not significantly improve predictions of the global network structure.

To summarize, taking into account the technological position of the firm in a model of alliance formation is informative on the relative network positions of the firms. For example, expected ranking of firms by closeness centrality becomes more like the observed ranking if technological position is taken into account. However, it is not informative for the distribution of network statistics in the network. For example, expected average closeness centrality does not further approach the observed level by taking into account the firm's technological position.

Chapter 4 considers the firm's embeddedness in the prior network of alliances next to the firm's position in technological space. The analysis follows exactly the analysis of the previous chapter. The main interests of the comparison are i) the relative effect of technological and social factors on alliance formation and ii) the extent to which social network effects in alliance formation influence higher-level network structures.

Results show that social and technological variables are similarly influential for pairwise alliance formation. The relevance of social network variables on alliance formation is in accord with several empirical studies (see e.g. Gulati and Gargiulo, 1999; Hallen, 2008; Rosenkopf and Padula, 2008). A further result is that technological proximity and social proximity do not moderate each other; there are no interaction effects. So they seem to be capturing two distinct, equally important, but independent drivers of firms' alliance decisions.

With respect to the firm's ego-network structure the social model and the technology model perform similarly well, the social model fits the data on ego-network structures somewhat better. The model of bilateral alliance formation which includes both types of factors predicts ego-network structures significantly better than models which take into account only one type of factor. At the global network level, compared to the technology model, including social factors in the model of alliance formation does not improve significantly the fit to the observed distribution of global network statistics.

Thus, introduction of social network variables in a model of pairwise alliance formation improves the fit on the alliance data but does not necessarily improve the fit on the observed network structure. This implies that the model and estimation approach is to some extent inconsistent. The social network variables are introduced in the regression because the network structure is considered to be relevant. Yet introduction of social network measures as regressors is not sufficient to obtain a model which is consistent with the network structure.

More importantly, simply improving model fit by introducing network statistics might misleadingly suggest that the network structure has a strong causal effect on alliance and network formation. The sensitivity analysis shows that the estimated effect of one social network measure, joint degree centrality, is spurious. This means that joint degree centrality captures not only the effect of the network on alliance formation (true path dependency) but also incorporates effects of stable, exogenous factors (spurious path dependency). This finding puts into question the estimates of all social network effects as estimated in this thesis and many other studies in the field (for example Ahuja, 2000; Gulati and Gargiulo, 1999; Powell et al., 2005). Therefore, an important issue for future research is to control for exogenous, stable structures which underly network formation. Underlying stable structures might be the technological space but stable economic characteristics as well might create the observed path dependency of network formation.

Chapter 5 investigates the division of innovative labor in the vaccine industry. This chapter deviates from the approach taken in the previous chapters in two respects. Firstly, the representation of the firm's technological knowledge is different. The chapter considers vaccines as nearly modular products which consist of distinct components. Therefore, we classify firms according to their technological competence in each component. Secondly, the focus is not on the network among individual firms but on the technology flow in the network among types of firms. The research question, however, remains similar compared to the previous chapters. How does the firm's technological specialization affect alliance formation and, in turn, influence higher-level network phenomena? In chapter 5, the higher-level phenomena of interest is the pattern of technology flow among different types of firms.

The empirical analysis found a significant technology flow from specialized, biotechnology firms to integrated, pharmaceutical firms. Part of the high in-sourcing activity is caused by the modular architecture of vaccines. One case on a pharmaceutical firm suggests that firms with large vaccine portfolios can take advantage of the modular architecture by in-sourcing vaccine components in order to enhance existing vaccines and develop novel vaccines.

Technology flow among specialized biotechnology firms is not clearly directed depending on the firm type. The argument that firms which are specialized in less substitutable vaccine components have higher bargaining-power and therefore attract technology has been weakly supported. Furthermore, the argument that competitive interdependence among firms with similar specialization results in a weak technology flow and symbiotic interdependence among firms with complementary specialization induces a strong technology flow is not supported by the data.

In order to better understand this result, the empirical analysis is complemented by the case of the biotechnology firm Crucell. Crucell's commercial success in licensing its transversal technology opened the route for product development and, later on, the acquisition of complementary resources for marketing and distribution. The case yields the important insight that the technological specialization of the firm does not predetermine its strategy and the role it is going to play in the industry.

The results of this thesis yield some general insights on how to understand alliance formation and its interaction with firms' technological and network characteristics, as well as how our empirical results on alliance formation can or cannot be used to understand aggregate network properties.

Firms are heterogeneous in their (technological, financial, business, and so on) endowments and the relative properties of two firms determine the benefit of an alliance between them. The pattern of how resources are distributed over firms provides a structure for alliance formation because the resource distribution assigns a potential alliance benefit to any two firms in the population. Thus, firms are positioned in a common space which relates all firms to each other. The thesis shows that the position of firms in technological space influences higher-level network structures. The insight that firms are located in a common environment whose structure affects the pattern of firm interaction will almost certainly apply to many more determinants of alliance formation. While we have addressed the issue of how technological endowments of firms affect alliance formation, and thus network structures, we have not investigated how alliance participation and network position affect a firm's technological endowments. They certainly co-evolve, but understanding this co-evolution remains a challenge.

For this endeavor, one needs to take into account that technological space is complex and high-dimensional. Formalization and measurement of technological space reduces this complexity. Necessarily, some aspects of technology are neglected by any measure whereas other aspects are captured. In the study, we found that different measures of technological distance yield different results. This suggests that firms care about many aspects of what we have called "technological fit" and that the way we formalize and measure technological space in general and technological fit in particular determines which aspects of technology are captured in the analysis. It is still an open question, how the different measures relate to each other, not at the technical level of how they are calculated, but how they need to be interpreted relative to each other. Furthermore, since they are likely to capture different aspects of technology, they might complement each other to obtain a more complete picture of the technological landscape and the relation of firms therein.

The firms' interaction does not only affect the technological space but, most directly, their social space which, in turn, affects alliance formation. Both technological and social factors have been found to be (equally) important but distinct and apparently independent. However, social network effects are special predictors of firm interaction in that they are usually measured on the aggregated outcome of firm interaction itself. This bears the risk of spurious path dependence. Stable network structures over time are probably caused by both true path dependence of network formation and stable, exogenous factors (possibly including slow-changing technological competences). Sorting out the path dependency effects from the influence of the (stable) distribution of heterogeneous resources is going to yield important management and policy implications. Therefore, spurious path dependency needs to be controlled for in network formation models. The discussion in the previous paragraphs opens up a potential route because it clarifies that in empirical research on interaction one does not need to control only for characteristics of the individual but one needs also to control for the latent structure which relates all individuals.

When researchers consider social network effects on alliances formation, they emphasize that firm interaction is a phenomenon which spans several levels which include alliances, ego-network structures and the global network of alliances. These levels are interconnected. This thesis first took a technical perspective. We argued that alliances are the elementary building blocks of a network and, therefore, models of alliance formation might be informative for higher-level network structures. We found that the alliance formation model has been informative for the firms' ego-network structures but less so for the global network structure. This exercise shows that models which focus at one level of the phenomenon, such as alliance formation models, might not generate a coherent picture of the whole network formation process. The lack of it indicates that something is missing and this is a valuable insight. The missing element might be further exogenous factors, besides technology. However, it might also be that interactions between the levels need to be taken into account. Something which to date, has either been ignored or assumed to be more or less automatic and thus not particularly interesting. The results obtained here suggest that neither is the case. An interesting starting point would be to stronger connect the decision of the firm on its alliance portfolio with the process of alliance formation. The firm is not an automaton. The firm's resource endowment and the environment it faces do not automatically imply a certain behavior of the firm. It is the strategy and internal working of the firm which links the firm's fundamentals with economic action. Incorporating the (diversity of the) strategies of the firms in theoretical models and empirical studies of alliance formation is an issue which has not been tackled in this thesis but deserves further attention.

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Abrégé de la Thèse

Le développement rapide de nouvelles technologies entraîne un accroissement constant des combinaisons technologiques des produits et des processus de production. Ce développement est à l'origine de l'entreprise multi-technologies, qui doit maîtriser de nombreuses technologies pour gérer et développer ses lignes de produits (voir Granstrand, 1998; Powell et al., 1996, par example). L'élargissement concomitant de la base de connaissances de l'entreprise finit cependant par lui créer un handicap, l'entreprise ne possédant plus les connaissances nécessaires à l'innovation. Les entreprises doivent pourtant innover afin de rester compétitives sur le marché. Pour ce faire elles doivent donc s'appuyer sur les connaissances complémentaires disponibles à l'extérieur de leurs frontières.

Les alliances sont fréquemment utilisées pour résoudre ce problème. Dans les alliances stratégiques, deux entreprises ou plus mettent leur ressources en commun, les échangent ou les partagent afin de renforcer leur base de connaissances ou de développer une activité conjointe. Les entreprises peuvent créer des alliances stratégiques à différents points de la chaîne de la valeur, de la recherche et développement (R&D) à la distribution, en passant par le marketing et la production. Cette thèse se focalise plus particulièrement sur les alliances de R&D qui génèrent transfert et partage de technologie, et R&D commune. Bien que les motivations à l'origine de la formation d'alliances de R&D soient diverses, les acteurs de l'industrie citent l'accès aux connaissances complémentaires comme le facteur le plus important (Hagedoorn, 1993; Herrling, 1998).[1] Les alliances sont particulièrement adaptées à cet objectif car

[1] Les alliances de R&D peuvent aussi être motivées par des considérations d'efficacité ou des interdépendances entre entreprises (see Hemphill and Vonortas, 2003). L'efficacité peut par exemple être améliorée par la réalisation d'économies d'échelle et de gamme, un meilleur accès au financement, ou l'utilisation de capacités supplémentaires. Dans les industries high-tech, où les alliances technologiques sont particulièrement nombreuses, l'accès aux connaissances complémentaires, une

la coopération entre entreprises peut être extrèmement efficace pour le transfert de connaissances tacites. L'élargissement de la base de connaissances induit ainsi des interactions entre les acteurs régulées par des alliances. Ce mécanisme peut expliquer le développement rapide des alliances de recherche depuis le milieu des années 1970.

La structure du réseau de recherche influence probablement la façon dont les connaisances sont créées et diffusée. Les études empiriques suggèrent que la position occupée par une entreprise au sein d'un réseau de recherche a une influence sur son comportement d'acquisition et de production des connaissances. Par exemple, les entreprises qui ont une position centrale dans le réseau et les entreprises membres d'un groupe très connecté peuvent présenter une productivité plus élevée de leurs activités de recherche (Ahuja, 2000). Comme la R&D commune génère des partage de connaissances et des spillovers, la structure du réseau peut aussi influencer la diffusion et l'accumulation de connaissances technologiques au sein du système (Cowan and Jonard, 2004). Dans ce contexte, la question du mode de formation des réseaux devient cruciale.

L'unité élémentaire du réseau étant l'alliance, les études portant sur la formation d'alliances apportent des éléments de réponse. Les études empiriques sur la formation d'alliances permettent d'estimer les facteurs expliquant pourquoi deux entreprises spécifiques vont former une alliance. La question est donc de savoir comment deux entreprises peuvent être technologiquement, économiquement et/ou socialement proches l'une de l'autre. Pour synthétiser cette littérature il est important de distinguer les études sur la formation des alliances de recherche et les études sur la formation d'alliances per se, qui peuvent inclure différents types d'alliances. D'une part, la littérature sur la formation d'alliances est très étendue alors que seulement quelques études sont consacrées à la formation d'alliances de recherche. D'autre part, et surtout, les deux courants de littérature suivent des approches différentes: la littérature sur les alliances de recherche se focalise sur le besoin de combiner les connaissances complémentaires alors que la littérature sur la formation d'alliances, plus étendue, s'intéresse principalement aux relations sociales des entreprises. Pour reprendre les termes de Eisenhardt and Schoonhoven (1996), la recherche sur les alliances de R&D se préoccuppe de l'incitation à la formation d'alliances, alors que la recherche sur les alliances per se s'intéresse principalement à l'opportunité de la formation d'alliances.

L'intérêt pour l'environnement social de l'entreprise au sein de l'analyse économique a été suscité par l'approche structuraliste en sociologie. Cette approche repose sur la conviction que l'individu est "purposeful and goal directed, guided by interests [...] and by the rewards and constraints imposed by the social environment." (Coleman, 1986, p.1310). La vision de l'action économique comme résultant d'incitations et d'opportunités n'est pas nouvelle en soi, et a été partagée par les premiers économistes

forme d'interdépendance, semble cependant être le facteur principal de formation d'alliances (Hagedoorn, 1993; Herrling, 1998).

tels Smith, Locke ou Mill (see Coleman, 1986, p.1310). La nouveauté vient plutôt de la conceptualisation de l'environnement social. Il est en effet conçu comme se réalisant à travers les relations existantes entre les individus. La structure du réseau social définit ainsi (localement) le fonctionnement des normes sociales, et chaque individu agit au sein de son propre environnement social local (Granovetter, 1985).

La prise en compte du contexte historique et social dans lequel les entreprises agissent a permis d'expliquer des comportements économiques observables incompatibles avec la perspective "traditionnelle" de l'acteur économique isolé, égoste et rationnel. La recherche sur les alliances devait par exemple expliquer pourquoi deux entreprises pouvaient investir dans du capital spécifique et échanger des connaissances dans le cadre de contrats incomplets. D'après la perspective "traditionnelle" de nombreux obstacles s'opposent à la formation d'alliances: deux entreprises étant deux entités légales aux intérêts divergeants, des problèmes d'appropriabilité (par exemple des fuites de connaissances) et d'aléa moral (par exemple des comportements opportunistes) peuvent apparaître (Williamson, 1991). De plus, l'information incomplète sur les partenaires potentiels réduit l'efficacité de la recherche de partenaire et des efforts permanents de coordination sont nécessaires au succès de l'alliance. Tous ces problèmes sont mieux appréhendés lorsque l'environnement social de l'entreprise est pris en compte. Les relations sociales et d'affaires sont une source d'information (fiable) et entretiennent les normes comportementales (Gulati, 1998).

La recherche empirique sur la formation d'alliances s'est focalisée sur les effets sociaux du réseau d'alliances antérieures. (Gulati and Gargiulo, 1999; Powell et al., 2005, sont probablement les plus représentatifs). L'argument sous-jacent est que même si le réseau d'alliances antérieures n'est pas l'environnement social complet, il en forme néanmoins une part importante. La méthode standard est de construire le réseau des alliances antérieures parmi un échantillon d'acteurs, de mesurer les statistiques de réseau spécifiques aux paires d'entreprises, et d'introduire ces statistiques comme variables indépendantes dans une régression dont la variable dépendante est la formation ou non d'une alliance. Les résultats empiriques suggèrent par exemple que la confiance, la réputation et le degré d'interconnexion des acteurs influencent la formation d'alliances (Gulati and Gargiulo, 1999). Bien que cette littérature reconnaisse pleinement le rôle des incitations et des opportunités, les facteurs incitatifs sont généralement traités comme de simples variables de contrôle. Les incitations stratégiques à la formation d'alliance sont ainsi prises en compte à travers des proxys généraux tels que, par exemple, le secteur industriel (Gulati and Gargiulo, 1999). La limite de cette littérature provient de ce qu'elle dérive le capital social de l'entreprise de la structure du réseau tout en approximant le premier par la seconde. Par exemple, la confiance mutuelle entre entreprises est à la fois supposée générée par la répétition des alliances et mesurée par le nombre d'alliances antérieures. Cette approche s'expose donc à des relations de causalité fallacieuses car des facteurs exogènes sont tout aussi susceptibles de générer des structures de réseau stables.

Les études empiriques sur la formation des alliances de recherche s'intéressent principalement à l'influence des dotations technologiques de deux entreprises sur leur décision de former une alliance. Pour ce faire il est d'abord nécessaire de savoir quelles combinaisons technologiques sont économiquement pertinentes. La plupart des études portant sur cette question sont parties du principe que le bénéfice de l'alliance dépend du rapport entre les connaissances des entreprises (see e.g. Cantwell and Colombo, 2000; Mowery et al., 1998; Rothaermel and Boeker, 2008). D'une part, les entreprises s'alliant pour accéder à des connaissances complémentaires, les bases de connaissances des entreprises partenaires doivent être différentes. Autrement dit, les nouvelles connaissances sont générées par la recombinaison de connaissances antérieures, et les nouvelles combinaisons ne sont possibles que dans la mesure où les bases de connaissances des entreprises sont différentes. D'autre part, les bases de connaissances doivent présenter certaines similarités car les capacités d'absorption des entreprises doivent être suffisamment élevées pour leur permettre d'évaluer leurs connaissances respectives et d'exploiter commercialement le résultat de la coopération (Cohen and Levinthal, 1990). Ainsi, les bases de connaissances des deux partenaires ne doivent être ni trop différentes ni trop similaires. La base de connaissances d'une entreprise est souvent mesurée à l'aide de son portefeuille de brevets. La proximité cognitive (technologique) est ensuite évaluée selon la proximité des portefeuilles de brevets. Cette proximité est par exemple révélée par un chevauchement des citations de brevets ou par des similarités dans les fréquences de dépôt de brevets dans certains domaines. Les résultats de ces études indiquent pour la plupart que la proximité technologique influence la formation d'alliances. A industrie, forme d'alliance (joint venture, accord de recherche) et mesure de distance données, ces études concluent que les entreprises qui sont à distance technologique proche ou intermédiaire sont les plus susceptibles de former une alliance (Mowery et al., 1998; Cantwell and Colombo, 2000, respectivement). Ces études ne tiennent cependant pas compte de l'influence du réseau d'alliances antérieures sur l'accès à l'information privée et la confiance.

L'alliance peut être considérée comme l'unité élémentaire du processus de formation de réseau. Un réseau est habituellement défini par un ensemble d'acteurs et de liens entre ces acteurs. La matrice d'adjacence contient toute ces informations. La matrice d'adjacence est une matrice binaire dont le nombre de lignes et de colonnes est égal au nombre d'acteurs. Une cellule de la matrice contient le chiffre un si une alliance existe entre les deux acteurs, zéro sinon.[2] Toutes les structures de réseau de niveau supérieur peuvent être extraites de la matrice d'adjacence. Le nombre d'alliances de l'entreprise correspond à la somme en ligne et en colonne. Le portefeuille d'alliances de l'entreprise

[2]Ceci est valable pour les réseaux "simples" avec un seul type de lien présent ou non et un ensemble d'acteurs qui ont formé des alliances pendant une période donnée. Des liens de types différents peuvent être représentés par plusieurs matrices, des liens de différentes valeurs par des cellules à entrées numériques, et la dynamique temporelle par l'empilement de matrices d'adjacence de différentes périodes.

est entièrement décrit en ligne et en colonne. Le réseau particulier d'une entreprise comprend l'ensemble de ses partenaires mais aussi les liens entre ces partenaires. Tous ces niveaux ont fait l'objet d'études empiriques, tant sur les alliances que les alliances de recherche.

Le nombre d'alliances d'une entreprise (ou taux de formation d'alliances) est l'indicateur le plus étudié(Ahuja, 2000; Powell et al., 1996; Shan et al., 1994; Walker et al., 1997; Zhang et al., 2007). Les entreprises dont le capital social ou le capital technologique est le plus développé sont aussi celles qui dont le nombre d'alliances est le plus élevé, ce qui confirme les résultats sur la formation d'alliances.[3] Le nombre d'alliances d'une entreprise est aussi positivement corrélé avec la densité des liens du voisinage social local et l'étendue de sa base de connaissances (Walker et al., 1997; Zhang et al., 2007, respectivement). On peut remarquer que, bien que les différents niveaux d'un réseau (alliance, réseau particulier d'une entreprise, etc...) soient connectés, les études empiriques se situent en général à l'un de ces niveaux d'analyse (voir chapitres 3 et 4). Une exception notoire est l'étude de Stuart (1998), qui porte sur l'influence de la dotation technologique d'une entreprise sur la formation d'alliances et sur le nombre d'alliances de l'entreprise. Il serait donc intéressant de savoir dans quelle mesure les résultats d'études portant sur différents niveaux peuvent être comparés. Par exemple, une étude empirique sur la formation d'alliances apporte-t-elle des éléments pertinents sur la façon dont la structure du réseau se forme?

Dans cette thèse, nous étudions la formation des réseaux de recherche industriels. Nous nous focalisons sur l'influence de l'hétérogénéité des capacités technologiques des entreprises sur leurs décisions de former des alliances, et par conséquent sur la structure du réseau. L'explication technologique de la formation de réseaux est complétée par la prise en compte des effets de la structure sociale héritée du réseau d'alliances antérieures. Nous faisons principalement appel à la littérature sur la formation d'alliances, à la théorie de l'entreprise basée sur les ressources, et à l'analyse des réseaux sociaux.

Le point de départ de cette thèse (chapitre 2) est un modèle théorique qui montre comment la dotation technologique des entreprises peut influencer la structure du réseau. L'hypothèse fondamentale de ce modèle est que le profit généré par la forma-

[3] Cette question a aussi été étudiée par Eisenhardt and Schoonhoven (1996). Cette étude est exceptionnelle à maints égards. Premièrement, tout comme Ahuja (2000), Eisenhardt and Schoonhoven (1996) étudient conjointement les facteurs sociaux et technologiques de la formation d'alliances. Deuxièmement, le capital social n'est pas mesuré selon le réseau d'alliances antérieures mais approximée par l'historique de carrière de l'équipe dirigeante. Troisièmement, cette étude n'évalue pas les compétences technologiques de l'entreprise selon son portefeuille de brevets mais selon sa stratégie technologique en s'appuyant sur des questionnaires et sur les caractéristiques des produits. Le problème de l'endogénéité du réseau est ainsi évité et la stratégie technologique de l'entreprise explicitement incluse.

tion d'une alliance entre deux entreprises est une fonction en forme de U inversé de leur distance technologique. La signification micro-économiques de cette hypothèse est l'arbitrage entre les capacités d'absorption et le potentiel de création de connaissances (Cohen and Levinthal, 1990; Nooteboom et al., 2007). Pour qu'une alliance soit rentable les deux doivent avoir des valeurs élevées mais les capacités d'absorption sont négativement corrélées avec la distance technologique, le potentiel de création de connaissance positivement. Ainsi, les bénéfices attendus d'une alliance sont selon toute vraisemblance les plus élevés à un point intermédiaire de la distance technologique. Le lien en forme de U inversé entre la distance et bénéfices retirés a été validé empiriquement par Mowery et al. (1998) et Nooteboom et al. (2007). Ces études montrent que les paires d'entreprises présentant une distance technologique intermédiaire sont les plus susceptibles de s'associer pour leurs activités de R&D. Notre modèle décrit comment la relation bénéfices-distance entre les entreprises paires façonne le réseau particulier des entreprises et la structure globale du réseau.

Le modèle repose sur l'hypothèse que les entreprises sont uniformément distribuées dans un espace technologique borné. Les entreprises maximisent leur profit en formant des alliances bilatérales. Le profit est supposé être une fonction en forme de U inversé de la distance technologique entre les firmes paires. Nous faisons de plus l'hypothèse que la formation d'une alliance génère un cot fixe. La spécification des profits et des cots implique que la formation d'une alliance n'est rentable que pour les paires d'entreprises séparées par un certain intervalle de distance, l'intervalle de distance rentable. Toutes les paires de firmes séparées par un intervalle de distance rentable forment une alliance. Ainsi, le réseau est complètement spécifié par la position des entreprises dans l'espace technologique et l'intervalle de distance rentable. Nous analysons comment les variations de l'intervalle de distance rentable génèrent différentes structures de réseau.

Notre modèle s'apparente au modèle de portefeuille de connaissances de Cowan and Jonard (2009) et au modèle de réseau social spatial de Gilles and Johnson (2000). Le modèle de portefeuille de connaissances applique la relation en forme de U inversé entre distance et les bénéfices dans un modèle évolutionniste. Les entreprises forment des alliances si leurs bases de connaissance se chevauchent suffisamment. En formant une alliance elles apprennent et accroissent le chevauchement de leurs bases. Cowan and Jonard (2009) montrent que pour certains intervalles de paramètres ce processus aboutit à des structures de réseau couramment observées empiriquement. Dans le modèle de réseau social spatial de Gilles and Johnson (2000), les agents sont distribués dans un espace social. Les agents retirent du profit des liens directs et indirects. Les cots de formation d'un lien sont fonction de la distance sociale entre deux agents. Carayol and Roux (2009) ont montré que le modèle de réseau social spatial, à l'instar du modèle de portefeuille de connaissances, peut produire des structures de réseaux comparables aux structures rélles observées.

La valeur ajoutée du modèle théorique proposé dans cette thèse est de déplacer l'analyse, de la structure globale du réseau vers le réseau particulier de l'entreprise. Notre analyse montre comment la position de l'entreprise au sein du réseau devient une fonction de la position de l'entreprise dans l'espace technologique. Le résultat central est que nous observons deux régimes différents selon la spécification de l'intervalle de distance rentable. Si les distances technologiques courtes (longues) sont propices à la formation d'alliances, alors les agents situés au centre (à la frontière) de l'espace technologique occupent une position centrale dans le réseau.

Le résultat du modèle est une illustration d'un principe plus général: l'hétérogénéité des dotations technologiques des entreprises implique une variabilité du nombre et de l'identité de leurs partenaires potentiels. Les différences en termes d'incitations à la formation d'alliances devraient selon toute vraisemblance se retrouver dans le réseau particulier des entreprises tout comme dans la structure globale du réseau. Le modèle théorique propose d'expliquer ce résultat par la dotation technologique des entreprises et la rentabilité des nouvelles combinaisons de connaissances.

Dans le chapitre 3, nous testons empiriquement l'effet de la distance technologique sur la formation de réseaux, dans le cas d'un réseau de recherche de l'industrie pharmaceutique. La révolution des biotechnologies a fragmenté l'espace cognitif de l'industrie pharmaceutique. Cela signifie que les entreprises ont des capacités technologiques hétérogènes et associent fréquemment leurs connaissances technologiques dans des alliances de recherche commune. De plus, l'utilisation généralisée du brevet dans cette industrie permet de mesurer facilement les connaissances technologiques d'une entreprise. L'industrie pharmaceutique est donc un domaine particulièrement intéressant pour tester notre modèle.

Le modèle théorique est testé en trois étapes. Tout d'abord, l'hypothèse fondamentale du modèle est validée en estimant l'effet de la distance technologique sur la formation d'alliances entre paires. L'estimateur assigne à chaque entreprise une probabilité de former une alliance. Suivant une approche Monte Carlo, les probabilités estimées sont ensuite utilisées pour simuler des réseaux dont sont extraites les valeurs espérées des statistiques de réseau. Les valeurs espérées et observées dans les réseaux particuliers des entreprises sont ensuite comparées. Enfin, nous comparons les valeurs espérées et observées du réseau global.[4]

Dans la première étape, la formation d'alliance entre paires d'entreprises est estimée avec un modèle logit. Le modèle contrôle l'interdépendance dyadique en introduisant des effets non observés spécifiques à l'entreprise. Une spécification à effets aléatoires (Hoff, 2003) est comparée à une spécification à effets fixes (Stuart, 1998) basée sur un test de Hausman simplifié. Au vu du résultat du test de Hausman, l'interprétation et les analyses suivantes sont basées sur la spécification à effets aléatoires.

[4] La simulation de réseaux basée sur les probabilités estimées des liens visant à comparer les statistiques du réseau global a été originellement proposée par Goodreau et al. (2007). A notre connaissance cette méthode est utilisée ici pour la première fois pour des réseaux d'alliances. De plus, nous étudions à la fois les réseaux particuliers et la structure globale du réseau.

La position technologique de l'entreprise est mesurée à l'aide de son portefeuille de brevets. Le portefeuille de brevets fournit l'information structurelle, les classes technologiques des brevets dans lesquelles l'entreprise brevète, et l'information quantitative, le nombre de brevets de l'entreprise. Ces informations sont utilisées pour indiquer la position technologique relative propre à chaque paire d'entreprise. La taille du portefeuille de brevets fournit deux variables: la taille conjointe et la différence de taille entre les portefeuilles de brevets des deux entreprises. La distance technologique est mesurée par le chevauchement, qui indique la mesure dans laquelle les deux entreprises brevètent dans les mêmes classes de brevets.

Les valeurs estimées suggèrent que la distance technologique a une relation en forme de U inversé avec la probabilité de formation d'alliance. La distance technologique optimale, distance à laquelle la formation d'une alliance est la plus probable, est relativement courte. Ce résultat renforce les conclusions de Mowery et al. (1998). L'analyse de sensibilité du modèle montre cependant que différentes mesures de la distance technologique génèrent des résultats différents. Nous avons construit deux mesures alternatives à la mesure basée sur le chevauchement: la corrélation non centrée et l'avantage technologique corrélé révélé. En utilisant l'avantage technologique corrélé révélé, les entreprises formant des alliances sont les entreprises les plus proches technologiquement, ce qui a aussi été observé par Stuart (1998). La corrélation non centrée des vecteurs de classes de brevets se révèle par contre non significative. Une interprétation possible de ce dernier résultat est que ces mesures reflètent des aspects différents de la distance technologique. Ces différents aspects n'étant pas tous également intéressants pour les entreprises, les différentes mesures de la distance technologique ne sont pas censés générer les mêmes résultats. On peut remarquer que si l'arbitrage entre les capacités d'absorption et le potentiel de création de connaissances implique le lien en forme de U inversé entre la distance et les bénéfices retirés il n'en est pas nécessairement la cause. Le même résultat peut par exemple être observé si la similarité entre portefeuilles de brevet indique simplement un intérêt commun pour certains domaines technologiques, ainsi que le suggèrent Zhang et al. (2007).

Dans les étapes suivantes de l'analyse nous avons utilisé les valeurs estimées avec la mesure de distance technologique basée sur le chevauchement. Pour cette mesure nous avons trouvé que la formation d'alliances est plus probable si la distance est relativement courte. Le modèle théorique implique que dans ce cas, les entreprises qui occupent une position centrale dans l'espace technologique occupent aussi une position centrale dans le réseau d'alliances. Les statistiques descriptives montrent que c'est le cas pour notre échantillon. Le modèle de formation d'alliances incluant les informations sur la position technologique de l'entreprise donne des résultats très proches des observations réelles sur les réseaux particuliers des entreprises. Cependant, la comparaison montre que le modèle incluant seulement les informations sur la taille du portefeuille de brevets donne des résultats presque aussi pertinents que le modèle de formation d'alliances incorporant les informations structurelles sur le chevauchement en plus des informations sur la taille. L'influence majeure observée ici de la taille du portefeuille de brevets d'une entreprise sur sa position dans le réseau corrobore les résultats de Ahuja (2000). En utilisant le nombre de brevets comme proxy pour le capital technologique de l'entreprise, Ahuja (2000) observe en effet une corrélation positive entre celui-ci et le nombre d'alliances de l'entreprise.

Au niveau du réseau, le modèle de formation d'alliances incluant la position technologique des entreprises n'améliore pas significativement les prédictions du modèle de base incluant seulement les informations sur la taille du portefeuille de brevets. Le modèle de base est suffisant pour générer des réseaux présentant une distribution du nombre d'alliances dans le réseau très proche de la distribution réelle observée. Concernant les distributions des autres statistiques de réseau, le modèle de base n'est que peu pertinent, au sens où les distributions observées et estimées des statistiques de réseau sont très différentes. Cependant, les informations sur la position technologique de l'entreprise n'améliorent pas significativement les prédictions du modèle de base.

Au total, la prise en compte de la position technologique de l'entreprise dans un modèle de formation d'alliances est pertinente pour estimer la position relative des entreprises dans le réseau. Par exemple, le classement simulé des entreprises selon leur proximité moyenne se rapproche du classement observé si la position technologique est prise en compte. Elle n'est cependant pas pertinente pour estimer la distribution des statistiques du réseau entier. Par exemple, la distribution simulée de la proximité moyenne n'est pas plus proche de la distribution observée lorsque la position technologique des entreprises est prise en compte. Autrement dit, le modèle de formation d'alliances incluant la position technologique des entreprises assigne correctement les entreprises à leur positions relatives dans un réseau spécifié de façon légèrement incorrecte.

Dans le chapitre 4 nous élargissons notre modèle pour y inclure l'intégration sociale (social embeddedness) de l'entreprise dans le réseau antérieur. L'analyse suit les mêmes étapes que celles du chapitre précédent. Les objectifs principaux de la comparaison sont de distinguer les effets des facteurs technologiques et sociaux de la formation d'alliances, et de savoir dans quelle mesure la prédiction des structures de réseau de niveau supérieur peut être améliorée par l'incorporation de mesures de l'intégration sociale dans les facteurs explicatifs de la formation d'alliances.

Nous nous référons à l'étude empirique de Gulati and Gargiulo (1999), qui a particulièrement influencé ce domaine. Gulati and Gargiulo (1999) distinguent trois types d'intégration sociale: deux entreprises ont développé une intégration relationnelle si elles ont un historique commun. L'intégration structurelle décrit la relation de deux entreprises avec leur environnement social commun. Enfin, l'intégration "positionnelle" relie l'entreprise au réseau social global. Pour chaque type d'intégration une variable est mesurée dans le réseau d'alliances antérieur. Il s'agit respectivement du nombre d'interactions passées (pour l'intégration relationnelle), du nombre de partenaires communs (pour l'intégration structurelle) et du nombre d'alliances passées (pour l'intégration positionnelle). Chaque entreprise est représentée par le nombre de ses alliances, un indicateur de "centralité de position". Cette information est utilisée pour associer à chaque paire d'entreprises les variables de "degré de centralité conjointe" et de "différence de degré de centralité".

Notre estimation tend à attribuer une importance égale aux facteurs sociaux et technologiques pour la formation des alliances. La distance technologique (chevauchement) et le nombre d'interactions passées influencent au même degré la formation d'alliances. Le degré de centralité conjointe et la différence en terme de nombre de brevets ont des effets marginaux de moindre amplitude. L'influence observée des variables de réseau sur la formation d'alliances est en accord avec les conclusions de plusieurs études empiriques (voir Gulati and Gargiulo, 1999; Hallen, 2008; Rosenkopf and Padula, 2008, par exmple). Un résultat complémentaire est que proximité technologique et proximité sociale ne s'annulent ni ne s'additionnent. Elles n'ont pas d'effet combiné.

De même que dans le chapitre précédent, nous avons ensuite utilisé les modèles estimés de formation d'alliances pour prédire les statistiques du réseau particulier de l'entreprise ainsi que la structure globale du réseau. En ce qui concerne le réseau particulier de l'entreprise, le modèle social et le modèle technologique donnent tous deux de bons résultats, le premier approchant sensiblement mieux les données réelles. Le modèle conjoint qui intègre les effets sociaux et technologiques améliore encore légèrement la qualité des prédictions. Le modèle de formation d'alliances intégrant les facteurs sociaux ne permet cependant pas d'améliorer la qualité de prédiction du modèle technologique en termes de distribution des statistiques du réseau global.

Le problème est que les variables de réseau sociales sont introduites dans la régression parce qu'elles sont censées être importantes dans le processus réel. La stratégie habituelle est d'intégrer le réseau dans le modèle sous la forme réduite de régresseurs. Il semble que cela ne soit pas suffisant pour obtenir un modèle cohérent avec la situation réelle (dont le réseau est un élément). Cet argument a déjà été souligné par Snijders et al. (2006), qui proposent de dépasser le problème en introduisant les statistiques de réseau suffisantes comme régresseurs supplémentaires dans un modèle de graphe aléatoire exponentiel. Cette approche est devenue possible seulement récemment pour des réseau de grande taille, et nous avons rencontré des problèmes majeurs de dégénérescence lorsque nous avons tenté de l'appliquer à notre modèle. Nos résultats soulignent cependant que les modèles de formation d'alliances ne sont pas de la même nature que les modèles de formation de réseaux, quels que soient les régresseurs entrant dans le modèle.

L'interprétation de nos résultats doit tenir compte de l'analyse de sensibilité, qui se heurte à un obstacle d'importance. L'analyse de sensibilité montre que l'effet estimé de l'une des statistiques de réseau, le degré de centralité conjointe, est fallacieux. Les variables de réseau sociales ne contiennent pas seulement l'effet du réseau (causalité réelle) mais aussi les effets de facteurs stables et exogènes (causalité fallacieuse). Ceci remet aussi en question l'effet estimé significatif des interactions antérieures, qui est un indicateur de la confiance entre les partenaires (Gulati, 1995a). Cette question de causalité fallacieuse se pose pour la plupart des études réalisées dans ce domaine, y compris dans des travaux très souvent cités portant par exemple sur les effets des réseaux sociaux sur la formation d'alliances (Gulati and Gargiulo, 1999), sur le choix de partenaire (Powell et al., 2005), ou encore sur le taux de formation d'alliances (Ahuja, 2000). Les travaux à venir devront donc s'attacher à intégrer des variables de contrôle pour les structures stables, exogènes, qui sous-tendent la formation de réseaux. Ces structures stables sous-jacentes peuvent être l'espace technologique, mais aussi des caractéristiques économiques structurelles à l'origine de causalités non observées dans la formation de réseaux.

Le chapitre 5 étudie la division du travail dans le processus d'innovation de l'industrie des vaccins. Ce chapitre se démarque doublement de l'approche suivie dans les chapitres précédents. Premièrement, les connaissances technologiques des entreprises sont représentées différemment. Les vaccins étant des produits presque modulaires composés d'éléments distincts, les entreprises sont classifiées selon les éléments pour lesquels elles possèdent des compétences technologiques. Deuxièmement, le chapitre 5 ne s'intéresse pas au réseau constitué par les entreprises individuellement mais aux flux technologiques entre différents types d'entreprises. Les flux technologiques sont mesurés selon le réseau d'alliances entre entreprises. La question principale reste cependant la même que dans les chapitres précédents: comment la spécialisation technologique de l'entreprise affecte-t-elle la formation d'alliances et, à travers celle-ci, les phénomènes de réseau de niveau supérieur. Dans ce cinquième chapitre, le phénomène de niveau supérieur considéré est la structure des flux technologiques entre les entreprises. L'analyse empirique a mis en évidence des flux technologiques particulièrement importants des entreprises de biotechnologies spécialisées vers les entreprises pharmaceutiques intégrées. Ce recours intensif aux technologies disponibles à l'extérieur de l'entreprise s'explique en partie par l'architecture modulaire des vaccins. L'étude d'une entreprise pharmaceutique suggère que les entreprises possédant un portefeuille de vaccins étendu peuvent tirer parti de cette architecture modulaire en se procurant des composants de vaccins pour améliorer les vaccins existants et en développer de nouveaux. Les flux technologiques entre les entreprises de biotechnologies spécialisées n'apparaissent pas clairement orientés par le type d'entreprise. L'argument selon lequel les entreprises spécialisées dans des composants de vaccin moins substituables ont un pouvoir de négociation plus élevé, et attirent donc davantage la technologie, n'est que très partiellement confirmé. L'argument selon lequel l'interdépendance concurrentielle entre les entreprises spécialisées dans les même domaines résulterait dans des flux technologiques faibles, et l'interdépendance symbiotique entre les entreprises spécialisées dans des domaines complémentaires résulterait dans des flux technologiques forts n'est pas confirmé par les données. Afin de mieux comprendre ce résultat, l'analyse empirique est complétée par une étude de cas portant sur l'entreprise de biotechnologies Crucell. Le succès obtenu par Crucell dans la commercialisation sous licence de sa technologie transversale lui a permis de se lancer dans le développement de produits, puis d'acquérir des ressources complémentaires en marketing et distribution. L'étude de cas a montré que la spécialisation technologique de l'entreprise ne permet de présager ni de sa stratégie ni du rôle qu'elle peut être amenée à jouer dans l'industrie.

Résumé

La généralisation rapide des alliances d'entreprises a généré de nombreux travaux de recherche visant à comprendre les causes et les effets de ce phénomène, alors que l'étude théorique et empirique de la formation des réseaux ne s'est développée que récemment. Cette thèse s'intéresse au rôle de la dotation technologique et sociale des entreprises dans leurs décisions de formation d'alliances bilatérales, et étudie comment les connaissances actuelles sur la formation d'alliances bilatérales peuvent aider à expliquer la structure du réseau d'alliances. Notre modèle théorique apporte un éclairage sur la façon dont la dotation technologique des entreprises affecte à la fois la structure globale du réseau et la position relative des entreprises au sein du réseau. Notre analyse empirique s'attache à estimer les effets de réseau technologiques et sociaux sur la formation d'alliances. Le pouvoir prédictif du modèle estimé s'avère élevé concernant la position de l'entreprise dans le réseau mais relativement faible concernant la structure globale du réseau.

Mots clés: alliances, formations des réseaux, ressources des firmes , réseaux sociaux.

Codes JEL: D21, D74, D85.

Abstract

The dramatic increase in alliances among firms has led to a large, and growing literature attempting to understand its causes and effects, whereas theoretical and empirical research on network formation is just at its beginnings. This thesis considers how the technological and social endowment of firms affect their decisions to form bilateral alliances, and investigates to what extent our knowledge on the formation of bilateral alliances helps to explain the structure of the alliance network. A theoretical model yields insights into how the technological endowment of firms may affect both the global network structure and the position of firms in the network. An empirical analysis estimates technological and social network effects on alliance formation. The estimated model is shown to be rather informative with respect to the firm's position in the network but not very informative with respect to the global network structure.

Keywords: Alliance formation, Network formation, Resource based view, Social networks.

JEL: D21, D74, D85.