Multi-causal Relationships between R&D Partnership Formation, Positional Embeddedness and Innovative Performance

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Abstract The main goal of this study is to develop an integral understanding of the relationships between alliances, positional embeddedness and innovative performance. Apart from a theoretical contribution, this research project specifically aims to make an empirical contribution. Overall, this paper makes two key contributions. First, following some recent suggestions for a more multiple causal approach (Grodal, 2004), this study will attempt to contribute to the above mentioned body of literature by empirically analyzing the multi-causal relationships and the resulting feedback loops between positional embeddedness, alliance formation and innovative performance of companies. Second, in order to be able to "link" the different studies with each other and to be able to draw some conclusions from this body of studies as a whole, we investigate the various relationships using one and the same dataset. Such a joint consideration of the three factors and their interaction, may also provide us with more insight in the validity of the arguments made by previous authors such as for instance Powell et al. (1996, 1999) and Ahuja (2000a, 2000b). The empirical setting of this study is a large international population of more than three thousand R&D partnerships taken from the MERIT-CATI database, established in four high-tech industries, during the period 1990-2000.

Interestingly, when combining the above discussed relationships, an important double feedback loop occurs. Not only does the formation of R&D partnerships increase innovation, which increases R&D partnership formation again, but R&D partnership formation also provides more central connectedness within the alliance network, which on its turn increases R&D partnership formation as well as innovation. The findings in this study support the so-called Matthew effect, refering to the situation in which already innovative companies constantly increase their innovative performance even further by increasing their level of R&D partnership formation and positional embeddedness. It is important for companies to be aware of the vicious cycle as discussed above. An implication of the above described model is that first movers and companies with a rich history of prior alliances will be at an advantage by establishing a central role within the alliance network earlier and thereby benefit from the double feedback loop of innovation. Managers could choose to anticipate such concerns about their participation in alliance networks by proactively initiate inter-firm contacts (preferable with central firms) in order to enhance their innovative capabilities and enable the further development of new alliances (see also Gulati, 1999).

Key words R&D partnership formation, Positional embeddedness, Innovation, Multi-causal relationships

1 Introduction

Knowledge is a central issue in research traditions that stress the importance of organizational learning and the transfer and diffusion of knowledge and innovative capabilities within a company and between companies (Grant, 1996). Organizational learning is based on the idea that a company's stock of knowledge evolves from its past achievements, and, in turn forms the foundation for a novel set of knowledge (Pennings and Harianto, 1992). The opportunities for organizational learning increase when a firm is exposed to new and diverse ideas, and thereby to new knowledge. New knowledge is said to be generated by the exchange and recombination of knowledge.

Making proper use of this new knowledge is found to be a relevant contribution to a firm's innovative performance (Cohen and Levinthal, 1989; Nonaka and Takeuchi, 1995; Pakes and Griliches, 1984). In this way, innovative performance can be defined as the output of a firm's underlying knowledge base (Griliches, 1984) and a firm's underlying dynamic capabilities by which companies alter their existing knowledge base (Eisenhardt and Martin, 2000). New knowledge can be generated

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within the firm (internally) or outside the firm (externally). External knowledge generation is based on differences in technological capabilities between firms. By making use of inter-firm collaborations, such as R&D partnerships, firms can learn from these differences, generate new ideas and practices, generate new knowledge and create incentives for innovative behavior (Ahuja, 2000a, Cohen and Levinthal, 1989, 1990). In other words, alliances can be seen as mechanisms to access or transfer new technological knowledge and to facilitate innovative efforts (Ahuja, 2000a; Baum, Calabrese and Silverman, 2000; Mody, 1993; Teece, 1992).

External knowledge generation by means of alliances has become more and more important during the last decades. This is related to important industrial and technological changes that have led to increased complexity, higher uncertainty surrounding R&D, increasing costs of R&D projects, and shortened innovation cycles that favor collaboration (see Contractor and Lorange, 1988; Dussauge and Garette, 1999; Hagedoorn, 1993, 1996; Mowery, 1988; Mytelka, 1991; Nooteboom, 1999; OECD, 1992).

However, not only the number of one-on-one alliances has become greater but firms are also increasingly embedded in networks of alliances (De Man, 2004). An important issue in that respect is the central position that a firm occupies within the alliance network since that determines its access to information and thereby to external knowledge. It is said that firms that occupy a central position within the alliance network are exposed to knowledge from a greater number of partner firms as well as from a greater variety of firms, and by this are more likely to increase their innovative activities (Powell et al., 1996)[5]. So, besides engaging into one-on-one alliances, occupying positional embeddedness within the network is expected to have a positive effect on innovative performance of companies as well.

Within the strategic management literature, a large amount of research has studied the relationships between alliances, positional embeddedness and innovation. One of the important gaps in our understanding about these relationships result from the fact that most of these studies focus on singular causal relationships (Grodal, 2004). Examples of some singular causal studies mentioned by Grodal (2004) are the impact of alliances on innovation (Ahuja, 2000a; Baum, Calabrese and Silverman, 2000; Kraatz, 1998; Shan, Walker and Kogut, 1994; Stuart, 2000; Walker, Kogut and Shan, 1997), the impact of positional embeddedness on innovation (Powell, Koput, Smith-Doerr and Owen-Smith, 1999), and the impact of innovation on alliances (Ahuja, 2000b; Stuart, 1998).

When studying this literature, we observe that the various relationships between alliance formation, positional embeddedness and innovation have been treated *only in pairs* thus far (thereby ignoring other relationships). Furthermore, the different studies investigating these various relationships all make use of a *specific* dataset. These datasets differ from each other, thereby making it difficult to get an overview of how the various relationships relate and complement each other. In order to be able to "link" the different studies with each other and to be able to draw some conclusions from this body of studies as a whole, there is a need to investigate the relationships using one and the same dataset. Such a joint consideration of the three factors and their interaction, may also provide us with more insight in the validity of the arguments made by previous authors such as for instance Powell et al. (1996, 1999) and Ahuja (2000a, 2000b). Powell et al. (1996, 1999) have found positive effects of positional embeddedness on a company's innovative performance. Ahuja has found positive effects of alliance formation on innovation (2000a) as well as positive effects of innovative performance on the formation of new alliances (2000b). The findings from previous literature all ignore one important issue, namely how do alliance formation, positional embeddedness and innovation relate and can they possibly complement one another?

The main goal of this study is to develop an integral understanding of the relationships between alliances, positional embeddedness and innovative performance. Apart from a theoretical contribution, this research project specifically aims to make an empirical contribution. The available empirical studies on this matter typically examine the relationship between two factors and do not incorporate the third one, let alone how they interact. Following some recent suggestions for a more multiple causal approach (Grodal, 2004), this study will attempt to contribute to the above mentioned body of literature by analyzing the *multi-causal* relationships and the resulting feedback loops between positional embeddedness, alliance formation and innovative performance of companies using *one and the same dataset*. The empirical setting of this study is a large international population of more than three thousand R&D partnerships taken from the MERIT CATI database (see Appendix A), established in four

[5] For a background in social network theory, see Knoke and Burt (1983) and Wasserman and Faust (1994).

high-tech industries, during the period 1990-2000. This paper includes more diverse sectors of industry in the analysis compared to previous literature, including the pharmaceutical (including biotech), computers, semiconductors and telecom industry.

Eisenhardt and Martin (2000) and Grant (1996) explain that particularly in rapidly changing environments, such as these high-tech industries, organizational learning and technological diversification are very important for effective innovative performance and the creation of a sustainable competitive advantage. In an environment in which technological innovation and the need for technological breadth is essential, companies will be more likely to form R&D alliances in order to acquire new innovation capabilities. As demonstrated in a number of studies, high-tech industries are a major area of industrial activity where companies forge an increasing number of partnerships (Chung, Singh and Lee, 2000; Gomes-Casseres, 1996; Hagedoorn, 2002). It is also in these industries, where a large number of companies are engaged in joint R&D through a variety of different modes of R&D partnerships (Hagedoorn 1993; Soh, 2003). Therefore, this study will concentrate on R&D partnerships within high-tech industries.

In the next section, we will first discuss the current literature on alliance formation, innovative performance, and positional embeddedness. The theoretical considerations and the corresponding hypotheses that we develop will focus on the expected effect that positional embeddedness, alliance formation, and a company's innovative activities might have on each other (singular relationships). This is followed by a discussion of the possible benefits of using multiple (instead of single) causal relationships between the above mentioned factors (see figure 1). The section on the research methods provides some details on the population, data sources, the independent and dependent variables, as well as the control variables used in the empirical analysis. This is followed by a presentation of the results, which are discussed further in the last section.

2 R&D Partnership Formation and Innovative Performance

2.1The effect of R&D partnership formation on innovation

The effect of R&D partnership formation on innovation is clearly embedded within the dynamic capabilities view of the firm and organizational learning theory. The dynamic capabilities view of the firm complements the resource-based view of the firm by presenting the dynamic aspect of the resources. It takes into account the factors surrounding resources, such as how resources are developed, how they are integrated within the firm, and how they are released. Dynamic capabilities are the ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments. The focus is on the drivers behind creation, evolution and competitive advantage (Teece et al., 1997). Dynamic resources help a firm to adjust its resource bundle and thereby to maintain the sustainability of its competitive advantage, which otherwise might be quickly eroded. The emphasis is not on a firm's current bundle of resources, but rather on the development and renewal of resources that alters the bundle of resources that a firm controls. Sometimes companies internally possess the right resources where a sustainable competitive advantage can be built on. But often firms need to adapt resources to the environment or gain access to new resources to leverage the existing ones. If a company can not internally develop critical knowledge or can not buy it in the market, an alliance is a good option to get access to resources and skills (assets and capabilities). Alliances can provide the benefit of resource sharing, allowing firms to (re)combine knowledge, skills and physical assets (know-how), as well as the benefit of getting access to knowledge spillovers (information) (Ahuja, 2000a).

Second, organizational learning is an important motive for the creation and use of alliances and closely connected to the resource based view of the firm and the dynamic capabilities view of the firm. R&D partnerships can be seen as a learning instrument through the exchange and imitation of resources that are embedded in the partner's organization (Kogut, 1988). In the literature, it is often mentioned that companies experiment with and learn from their contacts (see for instance Hagedoorn and Duysters, 2002). This learning opportunity allows firms to develop new capabilities that can be deployed throughout the organization, thereby extending its knowledge acquisition and innovative capabilities.

In a dynamic, technologically sophisticated, economic environment, learning through a variety of new contacts pays off, as this behavior can outperform short-term maximizing behavior that only concentrates on the efficiency of information transfer in existing contacts (Allen, 1988). Cooperation between companies in a dynamic environment with changing conditions encourages continuous learning by companies by helping them to learn different ways of doing things. Furthermore, it generates new ideas and new practices creating incentives for innovative behavior that further enhances their technological capabilities (Ahuja, 2000a; Barkema and Vermeulen, 1998; Cohen and Levinthal, 1989; 1990; McEvily and Zaheer, 1999).

Ahuja (2000a) explains that collaboration can affect a company's innovative performance in a positive way by providing several benefits. The first benefit is knowledge sharing. When companies engage into a R&D partnership with each other to develop a technology, the resultant knowledge is available to all the partners. So, R&D partnerships generate synergy effects. Second, by engaging into R&D partnerships, companies are able to bring together complementary skills which are necessary in the innovation process. By working together, companies can enjoy these economies of specialization without making any prior investments required for internal development. Furthermore, R&D partnerships enable companies to learn about the developed competencies of other companies which can enhance their own knowledge base and innovative performance. A third benefit deals with economies of scale. In case when larger research projects generate significantly more knowledge than smaller ones, or when there exist increasing returns so that the investment leads to a more than proportionate return in terms of innovation output, companies can take advantage of these economies of scale by engaging into R&D partnerships.

Previous literature has analyzed the consequences of the use of R&D partnerships on companies' innovative performance (Hagedoorn and Duysters, 2002; Hagedoorn and Schakenraad, 1994; Mowery et al., 1996). Several studies have been performed within different industries, which include, among others, biotechnology (Baum, Calabrese and Silverman, 2000, Powell et al., 1999; Shan, Walker and Kogut, 1994; Walker, Kogut and Shan, 1997), telecommunications (Godoe, 2000), semiconductors (Stuart, 2000), and chemicals (Ahuja, 2000a). All the above mentioned empirical studies find strong evidence of a positive effect of partnership formation on innovativeness. The diversity of research contexts may provide support for the generability of the findings of these studies (see also Grodal, 2004). Following the arguments mentioned in the above, the following hypothesis can be formulated:

Hypothesis 1: The higher the number of new R&D partnerships a company forms, the higher the likelihood that it has a higher innovative performance.

2.2 The effect of innovation on R&D partnership formation

As mentioned in the above, a wide range of studies has analyzed the effect of partnership formation on innovative performance within different industries using a variety of research contexts. However, there are just a few studies that have examined the opposite relationship, i.e. the impact of a company's innovations on its partnership formation. For example, Ahuja (2000b) concludes that a company's innovativeness has a significant positive impact on its partnership formation in the chemicals industry. Stuart (1998; 1999) and Podolny et al. (1996) report similar findings on factors that influence R&D partnerships in the semiconductor industry. Their studies show for instance that the number of technology alliances that were formed by a company was higher among the more innovative companies.

In general, companies that are innovative are expected to have a sound knowledge base and are expected to be capable of altering their existing knowledge base by acquiring and recombining knowledge in order to generate a new knowledge base. By working together with these kind of companies, a firm enhances its ability to increase and renew its own knowledge base and dynamic capabilities, thereby improving its own innovative performance. This makes innovative companies very attractive partners to engage with in new R&D partnerships. Hence:

Hypothesis 2: The higher a company's innovative performance, the higher the likelihood that it forms new R&D partnerships.

2.3 Positional Embeddedness

The literature mentioned above has been extended by linking a company's innovative performance not only to the frequency of its past alliances but also to the embeddedness of a company within its alliance network. Embeddedness refers to the structure of a network of social relations that can affect the economic actions, outcomes and behavior of a firm within the network, including its partners to whom it is (in)directly connected (Granovetter, 1992; Gulati, 1998), i.e. a company's position and embeddedness in networks of relationships (Zaheer and Zaheer, 1997).

The type of network in which a company is embedded defines the opportunities potentially available, while its position in that network structure and the types of inter-firm ties it maintains define its access to those opportunities (Uzzi, 1996). These networks are valuable conduits of information providing companies with both opportunities (for instance, competitive advantage, information and knowledge exchange, higher profitability, higher innovativeness) as well as constraints (for instance, a firm can be locked into undesirable strategic situations) and having important behavioral and performance implications for their alliances (Gulati, 1998; Gulati, Nohria and Zaheer, 2000). According to Baum, Calabrese and Silverman (2000), those configurations that provide access to more diverse information and capabilities per alliance, and thus produce desired benefits with minimum redundancy costs, conflicts, and complexity, will prove most beneficial for companies.

Several important research streams have emerged to define the literature of inter-actor embeddedness. The most dominant stream focuses on positional embeddedness, i.e. the position (i.e. centrality within the network) occupied by an actor in the network. Emphasis is on how position affects both actions and opportunities of an organizational actor (Burt, 1992; Uzzi, 1996; 1997), as well as its performance (Dacin, Ventresca and Beal, 1999).

2.4 The effect of positional embeddeness on innovation

Positional embeddedness refers to the position occupied by a firm in the network. The more connected a firm is with other contacts in the network (through direct ties with its alliance partners) and the more connected a firm's contacts are (through indirect ties with its partners' partners), the more central the position is that the firm occupies in the network, i.e. the higher the firm's positional embeddedness.

Companies that are more centrally located relative to other companies in the network can expect greater information benefits (Soh, 2003). First of all, the central position provides the company with access to a lot of (different) information sources. A company that moves to a more central position within the network is exposed to knowledge from a greater number of companies as well as from a greater variety of companies. Secondly, the central position also provides a way for evaluating and improving the information received from each source (Rowley, Behrens and Krackhardt, 2000). According to Bell (2005), central firms are more involved in their network (see also Wasserman and Faust, 1994), and by this are better able to compare information across sources, assess its veracity, are less likely to miss vital information, and can combine information in novel ways to generate innovation (Van de Ven, 1986).

Positional embeddedness provides access to and control over resources and by this is likely to be highly associated with innovation (Knoke and Burt, 1983; Powell et al., 1996; Wasserman and Faust, 1994). Powell et al. (1999) have analyzed the effect of positional embeddedness on company performance in the biotechnology industry between 1988 and 1997. They conclude that once companies move to a central position in the network, their innovative performance will increase. Positional embeddeness clearly enables a company to select and complete research projects that prove to be worthy of innovation. Ahuja (2000a) reports that both the number of direct ties and indirect ties (which can be seen as indicators of positional embeddedness) has a positive influence on a firm's innovative activities, i.e. innovation seems to need positional embeddeness. Following the above described literature, the following hypothesis can be formulated:

Hypothesis 3: The higher a company's positional embeddeness, the higher the likelihood that it has a higher innovative performance.

2.5 The effect of positional embeddeness on R&D partnership formation

The structural sociological perspective of alliance formation behavior argues that the patterns of inter-firm partnerships reflect the prior patterns of relationships (Gulati, 1995, 1999; Gulati and Gargiulo, 1999; Walter et al., 1997). A firm's ability to form new alliances is determined by the opportunities provided by its position in the prior network structure (Ahuja, 2000b). In the early stages of the evolution of a network, cooperation is based on direct relations and the structure is more or less governed by direct reciprocity. Over time, however, the reliance of companies on their previous relations for the choice of partners decreases. Third party relations and positions become more important for the choice of partners and companies within the alliance network may refer interesting partners to each other (Burt, 1992; Buskens and Raub, 2002; De Man, 2004; Lazega, 2000). Positional embeddedness increases the awareness of a company with respect to its possibilities to ally with other companies in the network and substitutes in part for personal experience with partners (Jansen, 2004).

Besides being aware of potential partners, companies must also have information about the needs, requirements, and reliability of these partners (Balakrishnan and Koza, 1993). Information about previous partners may be shared between the network members, thus making it easier to get in touch with new reliable partners (Burt, 1992; De Man, 2004). Access to valuable information like this can lower risks and their associated costs, and by this make it more likely to enter into new partnerships (Gulati, 1999).

So, positional embeddedness plays an important role in shaping the flow of information that enables companies to learn about *new* alliance opportunities with *reliable* partners (Buskens and Raub, 2002; Granovetter, 1985; Gulati, 1995; 1999; Kogut, Shan and Walker, 1992; Lazega, 2000) and has important behavioral and performance implications for companies' alliances (Gulati, 1998). Being embedded in a network of relations and having access to resources through different partners influences the decision of firms on whom to tie up with. Consequently, positional embeddedness is an important factor in explaining the alliance formation process (Gulati, 1995; Walker et al., 1997; Gulati and Gargiulo, 1999; Powell et al., 1996).

Evidence with respect to the effect of a firm's positional embeddedness on the likelihood of entering new alliances indeed reveals that central firms enter subsequent alliances more frequently than firms that are less central situated in the network (Eisenhardt and Schoonhoven, 1996; Gulati, 1997, 1999; Gulati and Gargiulo, 1999; Hagedoorn et al., 2006; Kogut et al, 1992; Podolny and Stuart, 1995; Powell et al., 1996; Powell et al., 1999). Furthermore, according to Lazzarini (2005), alliances are more likely to emerge when alliance networks exhibit a network structure characterized by high centralization. The effect of centralization suggests that the formation of alliances tends to be triggered by leading actors directly connected to other network members (Lazzarini, 2005). In line with the above mentioned arguments, the following hypothesis is formulated:

Hypothesis 4: The higher a company's positional embeddedness, the higher the likelihood that it forms new R&D partnerships.

2.6 The effect of R&D partnership formation on positional embeddedness

Previous studies show that firms with more prior partnerships, are more central in the network, and entered more frequent into new partnerships (Kogut et al, 1992; Gulati, 1997). The number of partnerships a company forms are clearly linked to positional embeddedness in a positive way. Powell et al. (1996) argue that the greater the number of partnerships, the higher the company's central connectedness, i.e. its positional embeddedness. Per definition, each new R&D partnership enhances the positional embeddedness of the participating companies by not only increasing the number of direct ties (with its partners) but also by increasing the number of indirect ties (with its partners' partners). Therefore, cooperative R&D increases positional embeddedness, although moving to a central position in the network takes time and involves multiple linkages with different partners (Powell et al., 1999). Hence:

Hypothesis 5: The higher the number of new R&D partnerships a company forms, the higher the likelihood that it has a higher positional embeddedness.

3 Introducing Multiple Causal Relationships

In order to capture the dynamics between positional embeddedness, R&D partnership formation and innovation, it is important to look at multiple causal relationships instead of just single causal relationships. The evidence of the singular causal relationships mentioned in the variety of empirical studies described above suggests a Matthew effect (Grodal, 2004; Merton, 1968). The basic idea of the Matthew effect is that of a positive (or negative) feedback loop in which the rich are getting richer and the poor are getting poorer. Here, the Matthew effect refers to the situation in which already dominant companies (i.e. innovative companies) constantly increase their innovative performance even further by increasing their level of alliance formation and positional embeddedness.

First, as has been described before, R&D partnership formation is expected to have a positive effect on a company's positional embeddedness (hypothesis 5). Furthermore, research has shown that a company's positional embeddedness within an alliance network facilitates innovative performance (hypothesis 3). Finally, innovative activity seems to foster the formation of new R&D partnerships (hypothesis 2). One part of the dynamic is that the combination of these singular causalities suggests a positive feedback loop between alliance formation and innovation. This means that companies with many partnerships will occupy a more central position within the alliance network, increasing their innovative performance, thereby favoring the formation of new alliances in the future.

Second, as already has been discussed, research has shown that positional embeddedness within an alliance network facilitates the formation of new alliances (hypothesis 4). Furthermore, alliance formation is expected to positively influence a company's innovative performance (hypothesis 1). This means that companies that are already in a more central position within an alliance network, will likely become more actively involved in inter-firm R&D partnerships, and thereby are expected to become increasingly innovative. The combination of the singular causalities as described above cover the other part of the dynamic by suggesting a second positive feedback loop between R&D alliances and innovation.

When combining the two feedback loops described above, an important double feedback loop occurs (see figure 1). Not only do innovative firms experience an increased likelihood of entering into new R&D partnerships, thereby enhancing their positional embeddedness which in the end affects innovative performance in a positive way. At the same time, being positional embedded within an alliance network facilitates the formation of R&D partnerships which in turn enhances the innovative performance of firms.

4 Research Methods

Data and sample

We present a statistical analysis of a large international population of 3124 R&D partnerships covering the years 1990-2000, which we obtained from the MERIT-CATI databank (see Appendix A). These 3124 partnerships are sponsored by 1697 companies from 39 countries. 18.76% of these R&D partnerships are joint ventures and 81.24% are contractual R&D partnerships. Furthermore, 47.25% of these R&D partnerships are domestic partnerships, whereas 52.75% have an international nature. We study four industries: pharmaceuticals (55.60% of the partnerships and 49.09 % of the total number of sponsoring companies), computers (10.63% and 13.80%), semi-conductors (27.08% and 27.39%), and telecom (6.69% and 9.72%). These industries are generally accepted as high-tech industries because of their R&D intensity, level of new product development, and patent intensity (OECD, 1992).

As already has been said, this study focuses on high-tech sectors and R&D partnerships because the research on alliances and innovation is consistent with the widely held belief that alliance networks form a "locus of innovation" in high-tech fields (Powell et al., 1996), with the emphasis on partnerships as mechanisms to access or transfer technological knowledge and to facilitate innovative efforts (Baum, Calabrese and Silverman, 2000; Mody, 1993; Teece, 1992). High-tech industries are a major area of industrial activity where companies forge an increasing number of partnerships (Chung, Singh and Lee, 2000; Gomes-Casseres, 1996; Hagedoorn, 2002) and it is in these industries where a large number of companies are engaged in joint R&D through a variety of different modes of R&D partnerships (Hagedoorn 1993; Soh, 2003).

Following some recent suggestions for a more multiple causal approach (Grodal, 2004), this study will attempt to contribute to the above mentioned body of literature by analyzing the *multi-causal* relationships and the resulting feedback loops between positional embeddedness, alliance formation and innovative performance of companies using *one and the same dataset*.

5 Variables and Method

5.1 Dependent and independent variables

This paper analyzes the existence of one model in which the singular causal relationships between positional embeddedness, R&D partnership formation, and innovative performance of companies are linked with each other (multi-causal perspective). Hypotheses 1-5 predict innovative performance, R&D partnership formation and positional embeddedness for companies in our sample. We take these in turn, meaning that these three variables in this study are both independent and dependent variables (see also Powell et al., 1996, 1999).

Innovative performance will be measured by counting the number of granted US patents from the US Patent and Trademark Office (USPTO) each company received per year. Several authors (Griliches, 1990; Kamien and Schwartz, 1982; Scherer and Ross, 1990) conclude that patents are an important measure of innovation output because they are directly related to inventiveness, they represent an externally validated measure of technological novelty, and they confer property rights on the assignee and therefore have economic significance. Research by Hagedoorn and Cloodt (2003) indicates that, in high-tech sectors such as those studied in this paper, counts of patents are adequate indicators of the overall technological performance of companies. In our study, US patents will be used because the US is the largest technology marketplace in the world, and it has become routine for non-US firms to patent in the US (Albert, Avery, Narin and McAllister, 1991).

R&D partnership formation will be measured by calculating the number of R&D alliances that each firm has formed in each year, starting in 1990 and ending in 2000. The focus is on high tech industries in which we find large numbers of inter-firm R&D partnerships, and where the interconnection between R&D partnerships formation and innovative performance is highly relevant and important. Furthermore, the focus of this study is on *newly formed* R&D partnerships, instead of total R&D partnerships as in other studies. The reason for this is that our main goal is to investigate multiple causal relationships and to prove the existence of the model as a whole. Innovativeness of firms is said to affect the formation of *new* alliances (not total alliances). Furthermore, *new* alliances alter a firm's positional embeddedness (by definition) and *new* alliances also enable access to new knowledge and thereby affect innovative performance. Besides, we are well aware of the additional effect of alliance experience as discussed in the literature, so we add partnership experience as one of the control variables in our study.

Positional embeddedness is measured by Freeman's (1979) closeness centrality measure using UCINET VI, a widely used network analysis program (Borgatti, Everett and Freeman, 2002). The measure we use is of a discrete nature. The measure is a variant of the measure used by Wasserman and Faust (1994) who use a relative measure. By using a discrete measure, all regression analyses can be performed by means of negative binomial models, thereby enhancing the comparison between the different models. Closeness is an inverse measure of centrality in that a larger value indicates a less central actor while a smaller value indicates a more central actor. Because our variable should measure centrality, a negative of the value is used to indicate that higher values indicate a more central position.

Closeness centrality may be defined as the total graph-theoretic distance of a given node from all other nodes. More precisely,

$$Ci = \sum_{j} dij$$

where d_{ij} is the number of links in the shortest path from actor i to actor j. Closeness centrality is a measure of independence from the control of others. It is a measure of network activity and measures how well connected a company is in the overall network. It is said that companies that are more embedded in the network have greater opportunities because they have choices. They may have access to, and be able to call on more resources (information, knowledge) of the network as a whole. This autonomy makes them less dependent on any specific other company, and hence more powerful (Hanneman, 2001). Contrary to degree centrality, closeness centrality focuses on the path rather than direct ties alone, so each specific company in the network is still considered to be connected (reachable) through intermediaries. Indeed, Gulati and Gargiulo (1999) show how companies benefit not just from their direct ties, but also from the ties of the companies to whom they are connected (i.e. their indirect ties). It is said that companies who are able to reach other companies at shorter path lengths or who are more reachable by other companies at shorter path lengths, have favored positions (Hanneman, 2001).

5.2 Control variables

Size is included as a control variable, because it is expected that the intensity of strategic technology alliances will increase with the size of the companies. Larger firms may have wider-reaching industry contacts and by this leading to more extensive networks and greater knowledge of alliance opportunities (Eisenhardt and Schoonhoven, 1996). Furthermore, the size of a company is said to have a positive effect on its innovative performance (George, Zahra and Wood, 2002). It is conventional to control for firm-size effects in analyses of innovative productivity (Cohen and Levin, 1989) and alliance activities (Gulati, 1999). In our study, the size of each company included in the database is measured by the natural logarithm of the number of employees. This information was accessed through the well-known databases Worldscope and Amadeus.

R&D Expenditures of companies are taken as a control variable because it is expected that their R&D expenditures are likely to be a determinant of their innovative performance. Studies by Griliches (1998), Hausman, Hall and Griliches (1984), Kamien and Schwartz (1982), and Scherer (1984) indicate a direct relation between the R&D efforts of companies and their patenting output, although the relation may not be a linear one. The variable R&D expenditures is measured by the natural logarithm of a firm's R&D expenditures on a yearly basis. In order to compare R&D expenditures of companies from different countries, all R&D expenditures are transformed into US$. This information was accessed through the well-known databases Worldscope and Amadeus.

Partnership Experience is included as a control variable because the experience of companies with setting up partnerships is known to affect their partnering behaviour positively (e.g. Ring and van de Ven, 1992; Gulati, 1995). Furthermore, the impact of collaboration on innovation increases in case companies have more alliance experience (Lane and Lubatkin, 1998; Mowery et al., 1996). Companies that have a lot of experience with managing alliances are for instance better able to reduce lead times or to integrate complementary knowledge which in the end may increase innovation (De Man and Duysters, 2005). The variable alliance experience refers to the natural logarithm of the number of years of alliance experience, which is measured as the time since the beginning of a company's first R&D partnership. This variable was calculated for each company in each year by subtracting the first year of alliance experience from the current year.

Sectoral Innovativeness is measured by the natural logarithm of the number of granted USPTO patents at the sector level for each year. This variable is included because the relevance of patenting differs between industries.

Network Centrality refers to the overall centralization of the network (sometimes referred to as global centrality) and is measured by the network centralization index using UCINET VI (Borgatti, Everett and Freeman, 2002). It measures how unequal the distribution of centrality is across all firms by measuring the extent to which the network as a whole looks like a star network. A star network is a network in which one actor is optimal central and connects to all other actors, i.e. the central actor acts as an intermediary for all other actors (Freeman, 1979; Hanneman, 2001). This variable is included in order to control for the possible effects that the degree of centrality at the network level has on a company's individual centrality level and its innovative performance. Structural network characteristics can affect the performance of the firms in an industry (Gulati et al., 2000, Meagher and Rogers, 2004; Walker et al., 1997).

5.3 Statistical method

All the dependent variables in our model are non-negative integer-valued count variables for R&D partnership formation, positional embeddedness, and innovative performance. Non-negative integer-valued count variables violate one of the main assumptions of the classical linear (OLS) regression model as the dependent variable can not be normally distributed. For such data, count models provide a methodological improvement over the classical linear regression model (Cameron and Trivedi, 1986; Gourieroux, Montfort and Trognon, 1984a and b; Hausman, Hall and Griliches, 1984). The Poisson model is the simplest and more restricted count data model that assumes equality of the conditional mean and variance. However, a large number of empirical distributions of count data have a variance greater than the mean and are thus over-dispersed relatively to the Poisson case (Cameron and Trivedi, 1986; Wooldridge, 2002). The negative binomial regression is an extension of the Poisson model and provides a mechanism for incorporating over-dispersion while allowing the variance of the process to differ from the mean (Cameron and Trivedi, 1986; Gourieroux et al., 1984a and b; Hausman et al., 1984).

The model as depicted in figure 1 is a recursive model because it contains lags. When looking at figure 1, it can be seen that for instance *R&D partnership formation at time t-1* has an effect on *innovative performance at time t* and *innovative performance at time t* has an effect again on *R&D partnership formation at time t+1*. It is clear that these different effects of R&D partnership formation and innovative performance on each other don't happen at the same time, i.e. they don't happen simultaneous. Furthermore, the model is clearly a recursive model, for instance because *R&D partnership formation at time t* is not determined by *positional embeddedness at time t*, and not a non-recursive model, or so-called simultaneous equation model.

In case of classical linear (OLS) data, the relationships between R&D partnership formation, positional embeddedness and innovative performance could be analyzed using path analysis. Unfortunately, it is not possible to perform path analysis with the dataset in this study for two reasons. First of all, as already has been explained, the variables in our model are non-negative integer-valued count variables, so we have to use a count model. Secondly, the arrows in the model should all lead to one (or several) dependent variable(s) and there should not be any arrows in the model that point in the opposite direction (in this case, the model will blow itself up because the beginning and the end of the model is not clear).

When performing three separate regressions with the use of count data analysis, the error terms of the three regressions could be correlated with each other. That's why it is important to perform a test which measures the correlations between the residuals of the three analyses. In case the correlations are low enough, the results of the regressions are reliable and can be used in order to explain the model as a whole.

6 Results

Table 1 presents the descriptive statistics and the correlations for the variables included in the analysis. The table suggests that there are no significant problems with multicollinearity across the main independent variables used in the negative binomial analyses. There is also little correlation between the independent variables and the control variables. One exception is the correlation between the variable patents on the one hand and some control variables (size and R&D expenditures) on the other hand, as well as the correlation between some control variables (size, R&D expenditures and alliance experience). This collinearity does not affect the coefficient estimates but it can affect the stability of the estimated coefficients (Ahuja and Katila, 2001). To ensure that our estimated coefficients are stable, we omitted one of the two correlated variables from our analysis. The results of the sensitivity analysis stayed the same for all but the omitted variable. In other words, the sign and the significance of the affected variables did not change and we can conclude that our results are robust. Therefore, we decided to include all control variables in our model since they represent theoretically different constructs.

Next, we have to choose which count model to use for our analysis. In order to choose between the Poisson model and the negative binomial model we tested the equality of the conditional mean and variance, which is the most important distributional assumption of the Poisson model. The tests show that our data are over-dispersed, the variance exceeds the mean, understating the computed standard errors in the Poisson regressions. In this case, the negative binomial model is to be preferred to the Poisson model for calculating the regression coefficients (Cameron and Trivedi, 1986).

As already has been said, hypotheses 1-5 predict innovative performance, R&D partnership formation and positional embeddedness for companies in our sample. We take these in turn, meaning that the variables in this study are both independent and dependent variables (see also Powell et al., 1996; 1999). Table 2 - 4 provide the estimation results of the negative binomial analyses. The first analysis deals with the effect of R&D partnership formation on positional embeddedness (table 2), the second analysis deals with the effect of innovative performance and positional embeddedness on R&D partnership formation (table 3), and the last analysis deals with the effect of R&D partnership formation and positional embeddedness on innovative performance (table 4).

The models in table 2 - 4[6] were significant overall, as indicated by the chi-square test using their log-likelihood values. The results from table 2 confirm hypothesis 5, which suggest that the more companies enter into new R&D alliances, the more these companies move to a more central position within the network. As can be seen from table 2, the formation of R&D alliances has a significant positive effect on the variables positional embeddedness at the 0.01 significance level.

The expected positive influence of innovative performance and positional embeddedness on the formation of new alliances is supported by the results in table 3 (hypotheses 2 and 4). The results show that the innovativeness has a significant positive effect on the formation of new R&D partnerships at the 0.05 significance level. This indicates that the more innovative companies are very attractive partners for engaging into new R&D partnerships. Furthermore, the effect of a company's central position within the network on alliance formation is also positively significant at the 0.05 level. Firms that are in a central position have better opportunities to engage into new R&D partnerships.

Hypothesis 1 and 3 state that the formation of R&D partnerships and the position a company has within the network have a positive effect on the company's innovative performance. The coefficient for R&D partnership formation is significant and positive at the 0.01 level, which clearly supports hypothesis 1 (see the results in table 4). Positional embeddedness is significant at the 0.05 level and has a positive effect on innovative performance, thereby supporting hypothesis 3.

Finally, we performed a test in order to check if the residuals of the three negative binomial analysis are not too much correlated with each other. Table 5 shows that the correlations between the three residuals are small enough to conclude that our results are reliable indeed.

To ensure the robustness of the findings, several control variables postulated in prior research were included. As expected, firm size shows significant positive effects on positional embeddedness as well as on innovative performance. Also, there exists a significant positive effect of R&D expenditures on R&D partnership formation as well as on innovative performance. The results indeed do confirm the expected positive effect of sectoral innovativeness on a firm's innovative performance. Furthermore, it turns out that there exists a significant positive effect of network centrality on positional embeddedness.

Somewhat surprisingly, the results show a negative effect of sectoral innovativeness on positional embeddedness and alliance formation by firms. Additional analysis with a squared term for this variable,

[6] Besides the results shown in table 2 - 4, we also performed additional analyses including interaction effects, sector dummies, year dummies and trend variables. The findings showed mixed results, which could be a consequence of right hand censoring and data limitations.

not reported here, does indicate a non-linear relationship between sectoral innovativeness and the two dependent variables. For companies active in an industry with a relatively low level of sectoral innovativeness, an increase in sectoral innovativeness will result in an increase in R&D partnership formation and positional embeddedness. However, for companies that are active in an industry that already has a relatively high level of sectoral innovativeness, a further increase in this innovativeness will have a negative effect on their R&D partnership formation and positional embeddedness.

The findings show no significant effects of size on the formation of R&D alliances, of network centrality on R&D partnership formation and innovative performance, and of R&D expenditures on positional embeddedness. The coefficient of partnership experience does not show any significant effects on the main variables, i.e. we cannot conclude that higher levels of partnership experience will result in higher R&D partnership formation, higher positional embeddedness and higher innovative performance. Hoang and Rothaermel (2005) have also found a non-significant effect of partnership experience of performance.

7 Discussion and Conclusions

Thus far, studies of the implications of postional embeddedness, R&D partnership formation and innovative performance on each other have proceeded separately, only looking at one singular relationship at a time. Yet, these singular relationships are interconnected with each other and merit consideration together. Based upon the earlier theoretical approach by Grodal (2004) and her suggestions for future research on the one hand, and the empirical findings of previous research as described above on the other hand, this paper contributes to the already existing literature. This research *empirically* analyzed the *multiple* causal relationships between alliances, innovation and positional embeddedness. This study is carried out for a large number of inter-firm R&D partnerships, from a variety of industries, from countries worldwide, over a long period of time, thereby contributing to the *generability* of the findings in the study.

When combining the above discussed relationships, two feedback loops occur (see figure 1). The first feedback loop shows that the formation of R&D alliances has significant positive effects on a company's network position. By engaging in new R&D alliances companies are able to move to a more central position within their alliance network, although this takes time and involves multiple linkages with different partners (Powell et al., 1999). Furthermore, the findings of this study show that positional embeddedness facilitates innovative performance (see also Ahuja, 2000a; Powell et al., 1999). Finally, innovative activity on its turn fosters the formation of new alliances. This indicates that the more innovative companies are very attractive partners for engaging into new R&D partnerships. Because by working together with this kind of companies, a firm can increase its own knowledge base and its own dynamic capabilities, and thereby enhancing its own innovative performance (see also Ahuja, 2000b; Stuart, 1998, 1999; Podolny et al., 1996). These results unfold the first positive feedback loop that exists between R&D partnership formation and innovative performance.

Furthermore, there exists a second positive feedback loop between a company's R&D alliance formation and its innovative activities. The findings from this study show that being centrally positioned within the network facilitates the formation of new alliances. These findings are consistent with the work of Eisenhardt and Schoonhoven (1996), Gulati (1997, 1999), Gulati and Gargiulo (1999), Hagedoorn et al. (2006), Kogut et al. (1992), Podolny and Stuart (1995) and Powell et al. (1996, 1999). Next to positional embeddedness on the firm level, network centrality also seems to play a role. There exists a positive effect of network centrality on the positional embeddedness of firms. A network that is highly centralized consists of a few central firms and many peripheral firms. Highly centralized networks provide a seemingly unlimited potential for novel combinations between firms. R&D partnerships are more likely to emerge when alliance networks exhibit a network structure characterized by high centralization. The effect of centralization suggests that the formation of alliances tends to be triggered by leading actors directly connected to other network members (Lazzarini, 2005). Firms may quit relations with less central players and invest in new relations with more central players, thereby increasing their own positional embeddedness. In seems that in highly centralized networks there is a greater need for individual firms to improve their own position within the network.

Besides, R&D partnership formation turns out to positively influence a company’s innovative performance. R&D partnerships act as mechanisms to access or transfer technological knowledge, to develop and maintain absorptive capacity and to facilitate innovative efforts (Ahuja, 2000a; Baum et al., 2000; Cohen and Levinthal, 1990; Mody, 1993; Powell et al., 1996; Stuart, 1998; Teece, 1992; Zaheer and Bell, 1995). This all means that companies that are already in a more central position within an alliance network, will likely become more actively involved in inter-firm R&D partnerships, and thereby are expected to become increasingly innovative. These findings are consistent with previous literature that show that firms with more prior partnerships, are more central in the network, and entered more frequent into new alliances (Kogut et al., 1992; Gulati, 1997). The combination of the singular causalities as described above cover the other part of the dynamic by revealing a second positive feedback loop between R&D alliances and innovation.

Interestingly, when combining the two feedback loops described above, an important double feedback loop occurs (see figure 1). Not only does the formation of R&D partnerships increase innovation, which increases R&D partnership formation again, but R&D partnership formation also provides more central connectedness within the alliance network, which on its turn increases R&D partnership formation as well as innovation. The findings in this study support the so-called Matthew effect, refering to the situation in which already innovative companies constantly increase their innovative performance even further by increasing their level of R&D partnership formation and postitional embeddedness.

In order to understand the relationships between R&D partnership formation, positional embeddedness and innovative performance, it is important for companies to be aware of the vicious cycle as discussed above. An implication of the above described model is that first movers will be at an advantage by establishing a central role within the alliance network earlier and thereby benefit from the double feedback loop of innovation. Firms with a rich history of prior alliances are likely to move to a more central position within their network and increase their innovative capabilities, thereby increasing the likelihood of becoming attractive partners for engaging into new alliances. Meanwhile, firms that do not participate that much into inter-firm partnerships may never be able to increase their innovative capabilities and may even never be able to get themselves to enter into a new alliance. Managers could choose to anticipate such concerns about their participation in alliance networks by proactively initiate inter-firm contacts (preferable with central firms) in order to enhance their innovative capabilities and enable the further development of new alliances (see also Gulati, 1999).

This study was the first attempt to analyze the relationships between R&D partnership formation, positional embeddedness and innovative performance using *multi-causal relationships* with the use of *one and the same dataset*. Future research could extend the current study by using these multi-causal relationships in order to find support for the idea of the existence of "one dynamic alliance-innovation model" (as suggested by Grodal, 2004), which shows a co-evolution of R&D alliance formation, positional embeddeness, and innovation within an alliance network context. A company's network position within an alliance network in particular, and the structure of the alliance network itself in general, are sensitive for changes. It is these structural changes that seem to raise the most fundamental strategic problems for companies in competition (see also Porter, 1981). Instead of using separate analyses as in the current study, future research could analyze the different relationships within one model, thereby revealing the consequences of the systemic dynamics of the model.

The current study concentrates on inter-firm R&D partnerships in high-tech industries (i.e. pharmaceuticals, telecom, computers and semiconductors) and the resulting effects of the multiple causal relationships between alliance formation, positional embeddedness and innovative performance. Future research could extend this study by examining these multiple causal relationships using a wider range of inter-firm partnerships that cover marketing or production and supply within a broader range of sectors (including medium- and low tech sectors). Also, a better understanding of the actual transfer of knowledge in R&D partnerships could benefit from research using a wider range of detailed firm-level indicators and more sophisticated sectoral characteristics than those currently available.

Furthermore, future research could include the effect of the diversity of ties (making a distinction between direct and indirect ties and/or between redundant and non-redundant ties) as additional or moderating factors in the model as analyzed in this study. When investigating the possible effects of these multiple causal relationships, future research could make a distinction between incremental innovations and radical innovations (that shape the future of industries, thereby altering the position of companies).

Another interesting topic of research would be the question what the magnitude of the different effects of R&D partnership formation, positional embeddedness and innovative performance are on each other. Does alliance formation and positional embeddedness indeed have such significant positive effects on innovative performance? Or could it maybe be that pre-alliance effects, such as the positional embeddedness and the patenting behaviour of the company *before* engaging into an alliance, are the dominant factor in explaining innovative performance. Our results show evidence for the so-called Matthew effect in which innovative companies increase there innovative performance even further. It would be interesting to investigate the effects of alliance formation and positional embeddedness on the innovative performance of companies when taking into account companies' pre-alliance positional embeddedness and pre-alliance innovation. Maybe alliance formation and positional embeddedness do not have that much an effect at all on innovation, but rather does innovation in the past lead to even more innovation in the future.

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Appendix A

The MERIT CATI database is a relational database which contains separate data files that can be linked to each other or to other databanks and provide both disaggregated and combined information from several files. So far information on around 12.000 technology-related inter-firm partnerships has been collected for the period 1960-2003. Systematic collection of inter-firm partnerships started in 1987. Many sources from earlier years are consulted to establish a retrospective view. In order to collect information on inter-firm partnerships various sources are consulted: newspaper and journal articles, books dealing with the subject, and in particular specialized journals which report on business events. Company annual reports, the financial rimes industrial companies yearbooks, and Dun and Bradstreet's "who owns whom" provide information about dissolved equity ventures and investments, as well a ventures that were not registered when surveying partnerships.

This method of information gathering which one can refer to as "literature-based alliance counting" has its drawbacks and limitations due to the lack of publicity for certain arrangements, low profile of certain groups of companies and field s of technology. Despite these shortcomings, which are largely unsolvable even in a situation of extensive and large-scale data-collection, this database is able to produce a clear picture of the joint efforts of many companies. This enables researchers to perform empirical research which goes beyond case studies. The database contains information on each agreement and some information on companies participating in these agreements. The first entity is the inter-firm cooperative agreement. Cooperative agreements are defines as common interests between independent (industrial) partners which are not connected through (majority) ownership. In the MERIT CATI database only those inter-firm agreements are being collected that contain some arrangements for transferring technology or joint research. Joint research pacts and second-source are clear-cut examples. Information is also collected on joint ventures in which new technology is receive from at least one of the partners, or joint ventures having some R&D program. Mere production or marketing joint ventures are excluded. In other words, this material is primarily related to R&D collaboration and technology cooperation, i.e. those agreements for which a combined innovative activity or an exchange of technology is at least part of the agreement (Hagedoorn, 2002).

Figures and Tables

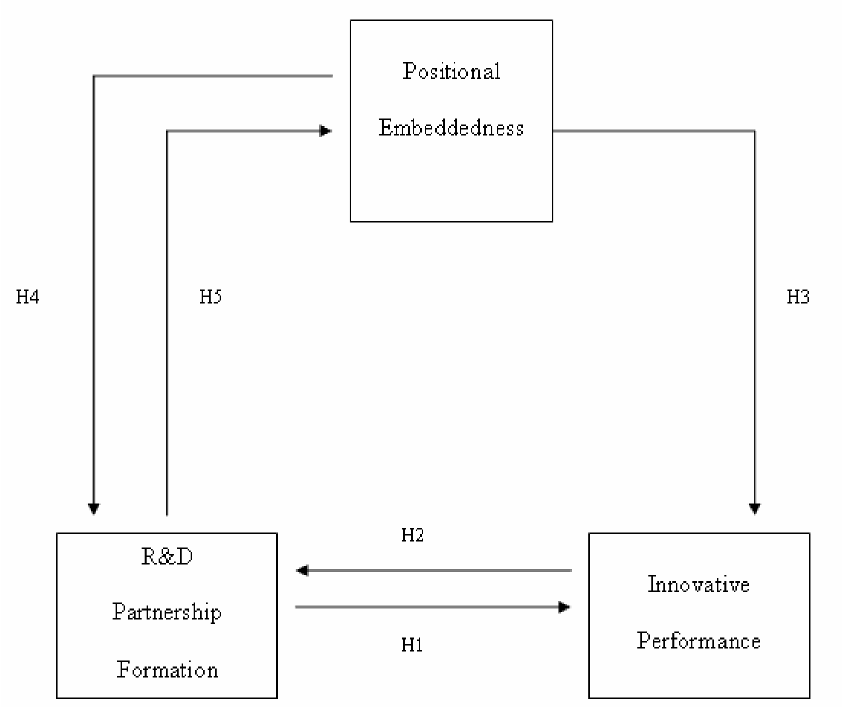

Figure 1 The multiple causal relationships between positional embeddedness, R&D partnership formation, and innovative performance

Table 1 Descriptive statistics (means and standard deviations (S.D.)) and bivariate correlations among all explanatory and control variables.[7] [8]

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1 R&D partnerships t	1.060	2.058	1.000										
2 Positional embeddedness t	88198.425	38133.178	0.306	1.000									
3 Innovative performance t-1	44.969	143.562	0.253	0.138	1.000								
4 Pos. embeddedness t-1	84320.596	37840.046	0.161	0.567	0.147	1.000							
5 R&D partnerships t-1	1.289	2.824	0.350	0.152	0.410	0.187	1.000						
6 Innovative performance t	47.093	148.742	0.267	0.130	0.983	0.144	0.432	1.000					
7 Size t	44524.635	91732.384	0.201	0.165	0.544	0.167	0.482	0.536	1.000				
8 R&D expenditures t	16.565	2.153	0.362	0.204	0.549	0.254	0.500	0.548	0.635	1.000			
9 Partnership experience t	6.041	8.265	0.216	0.089	0.379	0.151	0.287	0.352	0.441	0.582	1.000		
10 Sectoral innovativeness t	12817.262	9837.894	-0.060	-0.119	0.311	-0.035	0.153	0.339	0.333	0.120	0.037	1.000	
11 Network centrality t	0.017	0.009	0.056	0.154	0.054	0.274	0.135	0.036	0.072	0.100	-0.071	0.102	1.000

[7] For readability reasons, the correlations with the control variables are only shown at time t.
[8] The variables in table 1. are shown in the same order in which the three analyses mentioned earlier have been carried out.

Table 2 The effect of R&D partnership formation on positional embeddednes: results of the Negative Binomial Analysis

	Dependent Variable (at time t)
Predictor Variables (at time t)	Positional embeddedness
Constant	-10.4062****
	(0.4841)
R&D partnerships	0.0309***
	(0.0103)
Size	0.0600***
	(0.0212)
R&D expenditures	-0.0230
	(0.0246)
Partnership experience	-0.0049
	(0.0032)
Sectoral innovativeness	-0.1578***
	(0.0397)
Network centrality	23.6647****
	(3.7242)
Log L	-6357.699
Chi-square	9498284.0000****

Standard errors in parentheses.

**** significant at $p < 0.001$;
*** significant at $p < 0.01$;
** significant at $p < 0.05$;
* significant at $p < 0.10$.
~ multiplied by 1000 for readability reasons.

Table 3 The effect of innovative performance and positional embeddedness on R&D partnership formation: results of the Negative Binomial Analysis

	Dependent Variable (at time t)
Predictor Variables (at time t-1)	R&D partnerships
Constant	-2.4691**
	(1.1997)
Innovative performance	0.9524**~
	(0.4309)
Positional embeddedness	0.0036** ~
	(0.0017)
Size	-0.0015~
	(0.0391)
R&D expenditures	0.2237****
	(0.0633)
Partnership experience	-0.0032
	(0.0103)
Sectoral innovativeness	-0.0192**~
	(0.0089)
Network centrality	0.4434
	(10.3290)
Log L	-505.7087
Chi-square	137.8691****

Standard errors in parentheses.

**** significant at $p < 0.001$;
*** significant at $p < 0.01$;
** significant at $p < 0.05$;
* significant at $p < 0.10$.
~ multiplied by 1000 for readability reasons.

Table 4 The effect of R&D partnership formation and positional embeddedness on innovative performance: results of the Negative Binomial Analysis

	Dependent Variable (at time t)
Predictor Variables (at time t-1)	Innovative performance
Constant	-9.7032****
	(0.8723)
R&D partnerships	0.0349***
	(0.0125)
Positional embeddedness	0.0031***~
	(0.0012)
Size	0.1689****
	(0.0391)
R&D expenditures	0.4620****
	(0.0492)
Partnership experience	0.0054
	(0.0054)
Sectoral innovativeness	0.4512****
	(0.0645)
Network centrality	-0.7622
	(5.4921)
Log L	-2581.206
Chi-square	46372.490****

Standard errors in parentheses.

**** significant at $p < 0.001$;
*** significant at $p < 0.01$;
** significant at $p < 0.05$;
* significant at $p < 0.10$.
~ multiplied by 1000 for readability reasons.

Table 5 Descriptive statistics (means and standard deviations (S.D.)) and bivariate correlations between the residuals of the three negative binomial analyses (see table 2, 3, and 4).

Variable	Mean	S.D.	1	2	3
1 Residuals analysis 1 (see table 2)	-440.0203	36499.5832	1.000		
2 Residuals analysis 2 (see table 3)	0.0209	2.6581	-0.058	1.000	
3 Residuals analysis 3 (see table 4)	2.0201	150.1687	0.002	-0.018	1.000