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The Innovative Performance of Alliance Block Members: Evidence from the Microelectronics Industry

ABSTRACT

The primary goal of this paper is to improve our understanding of the relationship between the positioning of companies in technology alliance blocks –substructures in the alliance network- and their innovative performance. In particular, we expect that a firm's innovative performance depends partly on its position in specific alliance network settings: block membership or non-block membership. Firms in alliance blocks derive their competitive advantage from the superior and particular technologies they develop and exploit together. Incorporating the moderating effect of the degree of technological specialization in alliance blocks yields more insight in the contextual issues affecting the relationship between alliance block membership and innovation performance.

Keywords: strategic technology alliances, alliance block membership strategy, microelectronics industry, innovative performance, technology strategies

JEL codes: O31, O32

INTRODUCTION

The rapid increase in the number of newly established strategic alliances has led to the emergence of dense international strategic alliance networks (Chung et al.2000; Gomes-Casseres, 2003, 1996; Gulati, 1998). Firms have gradually become more and more embedded in dense inter-firm networks. In high tech sectors, we witness an increased fragmentation of alliance networks leading to an emergence of densely-tied substructures –alliance blocks- in these inter-firm networks (Gomes-Casseres, 1996; Rosenkopf and Padula, 2008; Vanhaverbeke and Noorderhaven, 2001). Some of the most successful firms have recognized that network positions in these densely tied substructures of the alliance network have allowed them to reap the full benefits from inter-firm alliances (Goerzen, 2007).

There is a fairly good understanding of why firms enter alliances and recent literature on strategic alliances has made significant progress in advancing our current understanding of who allies with whom. Scholars have been describing how social factors, social relations, status similarities and competitive tension between alliances affect the intent of creating, building and sustaining collaborative advantage through alliance formation (e.g Gulati, 1995, 1998; Walker, Kogut and Shan, 1997, Chung, Singh and Lee, 2000). This social structural context is an important driving factor in the alliance formation process (e.g. Gulati, 1995; Walker, Kogut and Shan, 1997; Chung, Singh and Lee, 2000). It specifically refers to with whom alliances are formed (Gulati et al., 1999) as firms have access to several partners with complementary assets, which influences the decision with whom to tie up. In this context, alliance formation is based on building preferential relationships that are characterized by trust, stability and rich exchange of information between partners (Powell, 1990; Gulati and Gargiulo, 1999). It asserts that network formation proceeds through the formation of new relationships, building on the experience with existing ties.

In the academic literature several authors have begun to study the effectiveness of network positions by examining the effects of relational and structural embeddedness on company performance (see e.g., Hagedoorn and Duysters, 2002a; Rowley et al., 2000). This is a debated issue, because in spite of a growing body of theoretical contributions (e.g. Rowley et al., 2000a; Uzzi, 1997; Walker et al., 1997; Hagedoorn and Duysters, 2002b), the empirical literature has been rather inconclusive about these effects.

Prior research indicates that alliance blocks –clique-like substructures in the alliance network composed of horizontal technology-based alliances- positively affect performance in industries such as healthcare (Provan and Sebastian, 1998), micro-processors (Gomes-Casseres, 1996), airline operations (Lazzarini, 2007) and investment banking (Rowley et al., 2004). Past clique studies found positive effects of clique membership on financial and operational performance (Rowley et al., 2004; Lazzarini, 2007), but the effects of alliance block membership on *innovation* performance remains rather unclear. Also the question if and under what conditions alliance block membership affects innovative performance remains largely unexplored. Then, prior work has paid less attention to the manner in which firm-level characteristics affect partner choice and innovative performance. Moreover, firm-level ego networks and industry-level interfirm networks are increasingly better understood than the role of network substructures - like cliques or alliance blocks- that lie in between these distinct levels of analysis (Rowley et al., 2004). The effectiveness of a firm's participation in technology alliances could be unevenly distributed, because companies show variations in terms of the substructures in which they are embedded.

In this paper we are interested in the effects of strong forms of network embeddedness -alliance network substructures that we refer to as alliance blocks- on *innovation* performance of firms. We investigate whether and under which conditions alliance block membership affects innovative performance.

We suggest a number of hypotheses, derived from our current understanding of some basic relationships between alliance block membership and innovative performance. We study strategic technology alliances -horizontal alliances in the pre-competitive phase of the value chain- which are 'modes of inter-firm cooperation for which a combined innovative activity or an exchange of technology is at least part of an agreement' (Hagedoorn and Duysters, 2002a). Our main argument is that the effect of network positioning of companies on their innovative performance depends on both their position in one of two basic network settings -block membership or non-block membership. Incorporating the moderating effect of the degree of technological specialization in alliance blocks seems to be a major step into discovering the contextual issues that prevents previous research from drawing clear-cut and generalizable conclusions.

HYPOTHESES

The Emergence of Alliance Blocks

Alliance groups derive their competitive advantage from their superior and particular technologies, which they develop and exploit together. These alliance blocks consist of technology alliances with firms that are often competitors in the market place, but are partners in the pre-competitive phase of technology development, i.e. when working together on R&D or for setting technology standards in an industry. This type of technology alliance actually refers to a horizontal alliance. Philips for example works together with Sony and Samsung to develop the Blue Ray Disc standard. This implies that these alliance partners collaborate in the pre-competitive phase of the technology development to reduce risk and share the huge research costs related to early technology development, although they are competitors in the subsequent commercialization phase. This can result in technological standard battles among alliance groups and independent firms (Gomes-Casseres 1996; Das and Teng 2002).

An alliance block or constellation [1] is 'an alternative to the single firm as a way of governing a bundle of capabilities' (Gomes-Casseres, 2003: 328). This concept is not comparable to 'industry clusters' which are geographically bounded networks of firms (Bell, 2005; Saxenian, 1994) and where the group of firms is linked through horizontal alliances on the one hand and vertical alliances with suppliers or customers on the other hand. Nohria and Garcia-Pont (1991, p. 106) define a strategic alliance block as "...a set of firms that are connected more densely to each other than to other firms in the industry". The existence of strategic blocks of firms was already anticipated by Harrigan (1985) who described them as constellations of firms. Empirical analyses of strategic blocks in different industries can be found in Nohria and Garcia-Pont (1991), Gomes-Casseres (1996) and Vanhaverbeke and Noorderhaven (2001).

The social network perspective we adopt to study alliance networks and substructures (like alliance blocks), addresses the social structural context driving the alliance formation process (e.g. Gulati, 1998). The perspective posits that actors are embedded in a network of social relationships. Embeddedness refers to the structure of a network of social relations that can affect the firm's economic action, outcomes and behaviour and that of its partners. Embeddedness influences the firms' tying behaviour, because it enables preferential relations to emerge from the direct and indirect contacts firms have built up in previous partnerships built on high levels of familiarity, trust and mutual understanding. These social factors make existing relations efficient to establish and easy to maintain. They have a strong influence on the choice of future partners (Gulati, 1995; Walker et al., 1997) as they reduce transaction costs. By investing in relation-specific resources through repeatedly engaging in alliances with the same partner (s), firms build up social capital (Burt, 1992). Social capital captures the shared values, norms and trust between alliance partners and is thus by its very nature dependent on prior events (Chung, Sing and Lee, 2000). As a result, partner choice is path-dependent as it is strongly based on social factors. Social capital drives the network to self-organize, self-transform and self-reinforce, as social capital forms the basis upon which the actors establish future social relations (Gulati, 1998).

The network becomes a growing repository of information on the availability, reputation, competencies and reliability of prospective partners (Gulati, 1995). This process typically leads to the formation of substructures in the inter-firm network - densely connected blocks of collaborative relationships- consisting of firms that are all mutually connected through multiple alliances. An alliance block is generally considered as one of the strongest forms of social embeddedness of companies. In this regard, looking at alliance blocks from a social network perspective, alliance blocks are ‘cohesive subgroups in a social network which are characterized by a very dense network of ties within the subgroup as compared to the relatively sparse networks of ties outside the subgroup’ (Wasserman and Faust, 1994: 267). The main characteristic of an alliance block or a cohesive subgroup in a social network is that it is generally characterized by a multitude of relatively strong ties (Nohria and Garcia-Pont, 1991; Vanhaverbeke and Noorderhaven, 2001) and that the relationships among its members are more important and more numerous than the relationships between members and non-members (Fershtman, 1997). Alliance block members seem to maintain and replicate strong and multiple ties within their group. Alliance blocks can be distinguished from other parts of the network by their large number of within group ties with few relations outside the group (Nohria and Garcia-Pont, 1991). So the density *within* the groups is high and low *between* the groups (Baum et al, 2003; Schilling and Phelps, 2004; Watts, 1999). They are viewed as one of the most powerful sources of embeddedness since these firms are mainly influenced by its most direct set of business partners (Pieters, 2009). The concept of alliance blocks is also related to the ‘small worlds’ concept, which indicates that the inter-organizational network is characterized by clique-like groups of firms.

Alliance Block Membership and Innovative Performance

The effect of block membership on the innovative performance can be seen in the light of the current debate on the advantages and disadvantages of the degree of social embeddedness and tie-strength. In this debate on the role of social embeddedness (e.g., Rowley et al., 2000; Gargiulo and Benassi, 2000) the basic arguments stem from Burt's (1992) structural hole argument versus Coleman's (1988) closure argument. Burt (1992) suggests that firms embedded in sparsely connected networks will enjoy brokerage advantages based on access to non-redundant information (see also Rowley et al., 2000). Hence, strategic opportunities increase as firms form bridges between densely connected parts of the network to other parts of the network through non-redundant ties (Burt, 1992; Walker et al., 1997).

Such strategies in which firms cross structural holes enable them to access knowledge that is expected to be more effective than strategies in which companies rely heavily on redundant ties.

Alternatively, Coleman (1988) argues that being part of a dense and apparently somewhat redundant network - like in an alliance block - is advantageous since it involves trust and cooperation among its members. As argued, alliance blocks constitute the strongest form of embeddedness and are therefore a particular case-in-point. Increased cooperation in such alliance blocks consisting of trusting partners is then expected to generate high spill-over effects among network participants that also increase the performance of their joint activities.

Firms frequently select partners based on their network of prior ties (Gulati and Gargiulo, 1999; Goerzen, 2007) where partner selection depends on the embedded social relations that a firm is already engaged in (Granovetter, 1985; Gulati, 1998). Relation-specific investments made in the past, increase the economic interests at stake, and, when balanced between partners, can demonstrate mutual commitment. This further stimulates the relationship in terms of reciprocity, which lays the foundation for future interactions and hence for the deepening of mutual knowledge (Capaldo, 2007). This repeated tie effect can create strong cohesive ties through frequent interaction. These strong ties are solid and reciprocal relationships that create a basis of trust and intimacy between partners (Granovetter, 1973; Brass et al., 1998).

When firms have invested a substantial amount of time and energy in order to establish these strong relationships, changing partners in the short run is not very likely, as it involves substantial switching costs and it increases the risk that other existing relationships with its partners will also dissolve (Chung et al., 2000). As a consequence, firms prefer to engage in local search and replicate their existing ties rather than search for new ones (Gulati, 1995, 1998; Walker et al., 1997). In the context of innovative activities, firms use these local search strategies to initiate new joint R&D projects that share common technological characteristics with those of their prior partners (Stuart and Podolny, 1996). This local search process requires some pre-alliance technological overlap (Lane and

Lubatkin, 1998; Mowery et al., 1996; Nooteboom et al. 2007) or similarity in R&D activities (Rosenkopf and Nerkar, 2001) in order for firms to assimilate and understand the technology that firms can access through their ties (Duysters and Lemmens, 2003). Formation of ties with similar others leads to alignment of interests; it facilitates mobilization and pooling of resources aimed at establishing dominance in the industry. Such joint and coordinated action facilitates the exploitation of existing technologies and organizational practices resulting in competitive advantage (Koka, Prescott, 2008). Similarity thus encourages interaction, which can be seen as the main cause of attraction. Prior research has suggested that homophily -the propensity for similar firms to link-up- is an important determinant in the formation of inter-organizational relationships (Wholey and Huonker, 1993; Goerzen, 2007, Ahuja et al. 2009). This process is referred to as 'interaction breeds similarity' and 'similarity breeds attraction' (Brass et al., 1998). In this context of local search and similarity, firms maintain and replicate strong and multiple ties, which lead to the formation of densely connected alliance groups. Thus, the more alliance block members will replicate their existing ties within their group, the higher the density of their in-group ties, which will result in a higher level of embeddedness within the group (Gomes-Casseres, 1996; see Knoke and Kuklinski, 1982 for a more general social network perspective).

Since trust emerges from repeated interactions, it is an important basis for knowledge sharing and joint learning (Brass et al., 1998; Nooteboom, 2002). Firms use their strong and trustworthy relationships in the alliances within groups of collaborating companies (alliance blocks) to take advantage of knowledge spillovers to improve their innovative performance (Vanhaverbeke and Noorderhaven, 2001). Network resources provided by partners in the local alliance network can enhance the focal firm's performance and value-creation. Resources are leveraged and internalized through learning and imitation (Lavie, 2008). R&D investments made by partner block members create spillover effects in the sense that other block members receive more new knowledge in return than firms which are not embedded in an alliance block (Vanhaverbeke et al., 2008).

Thus, firms that follow an innovation strategy outside of alliance blocks cannot take advantage of network externalities and knowledge spillovers that multiple, embedded ties provide for alliance block members. These non-block members lack the densely connected web of ties that constitutes a learning environment founded on trust-based governance, which is required for technological learning (Gomes-Casseres, 2001; Vanhaverbeke and Noorderhaven, 2001).

In other words, given the cohesion and familiarity of group-members based on their multiple, embedded ties in alliance blocks, companies with joint innovative activities that share knowledge within these alliance blocks are expected to generate higher innovative performance than firms positioned outside of alliance blocks. Non-block companies will have a hard time to individually coordinate and connect these incremental innovations (Chesbrough and Teece, 1996) as they follow individual innovation strategies outside of alliance blocks. They spend a substantial amount of resources on individual projects under conditions where joint, incremental innovations are more effective. As a result, we posit the following hypothesis:

H1: *Members of alliance blocks have a higher innovative performance than non-alliance block firms.*

Although we hypothesize a positive effect of replication of ties on innovation performance of alliance partners, there is also a downside to repeated partnerships. Goerzen (2007) addresses this duality of the effect of replication of ties with prior partners and its effect on performance. Repeated ties with previous partners reduce transaction costs and improve alliance integration, which should have a positive effect on performance as we mentioned in Hypothesis 1. Search costs are minimized, trustworthiness is established and given mutual understanding, managerial efficiency is increased. On the other hand, firms that engage solely in exploitation through the replication of ties may find themselves trapped in sub-optimal equilibria (March, 1971). Therefore, we expect that the benefits of alliance block membership are not distributed in a uniform way over time. Joining an alliance block provides the strongest benefits for the company immediately after it becomes a member of the block. The new environment and the abundance of new (indirect) ties increase the likelihood that the firm discovers and exploits new opportunities. Over time, the benefits of being a block member will level off over time as firms may start to suffer from relational 'over-embeddedness' (Uzzi, 1997), caused by relational inertia and the increasingly redundant similarity of firms within alliance blocks. Too much familiarity may reduce the innovative steam from collaboration. The positive effect of an alliance block membership strategy based on the replication of preferential relations can thus turn into a paralyzing effect as firms become locked-in in their own closed social system (Duysters and Lemmens, 2003). This paralyzing effect can be caused by relational inertia on the one hand and technological over-embeddedness on the other hand:

Relational Inertia

Relational inertia occurs when block members are constrained in their partner choice when linking up with firms of another alliance block or 'outsiders' in general (Gomes-Casseres, 1996). Over time, they may experience implicit social pressure from their partners to replicate their ties within the alliance block (Duysters and Lemmens, 2003) in order to prevent knowledge leakage outside of the alliance block. An implicit expectation of loyalty to other block members can prevent block members from allying with firms from competing alliance blocks (Gulati et al., 2000) as this can result in conflicting interests among its partners (Nohria and Garcia-Pont, 1991). Hence, certain potential partners outside of an alliance block are not available when they have ties to 'outside' competitors of block members. In this way, competing alliance blocks can foreclose further partnering opportunities from non-block members (Gomes-Casseres, 1996). As a consequence, potential partners outside alliance blocks are simply excluded from partner selection and, based on their initial choices, firms can become locked-in their own alliance blocks. This phenomenon of strategic gridlock (Gomes-Casseres, 1996) forces blocks members to engage in local search for partners within their own alliance block, which can make them both relationally inert and over-embedded.

Technological Over-Embeddedness

The repeated tie effect in alliance blocks can also lead to an increasing similarity in technology profiles and can eventually result in technological over-embeddedness (Uzzi, 1997). In that context, the block members' post-alliance technological profiles converge and they will become increasingly similar. In the long run this will decrease potential learning effects among alliance partners (Mowery et al., 1996; Duysters and Lemmens, 2003) as too much focus on developing competences through local search can lead firms to develop collective blindness, turn technological competencies into core rigidities (Leonard-Barton, 1995) and cause firms to fall into competency traps (Levitt and March, 1988). This rigidity among block members will increase the likelihood that they become cognitively locked-in (Uzzi, 1997; Gargiulo and Benassi, 2000). As a consequence, firms in alliance blocks tend to gradually become more restrained in taking advantage of new technological opportunities and resource niches.

In terms of learning we expect that, over time, both relational and technological over-embeddedness lead to decreasing opportunities for learning and innovation. Hence, we expect a negative relationship between the *duration* of a firm's membership in an alliance block and its innovative performance. Therefore, we hypothesize:

H2: There is a negative relationship between the duration of a company's alliance block membership and its innovative performance.

Technological specialization of alliance block members

Block membership provides access to knowledge and skills to speed up the innovation process and enables firms to transfer knowledge and replenish their knowledge bases (Mowery et al. 1996; Kogut

1988). In this way, firms can internalize the competencies of partners to create next-generation competencies (Hamel 1991; Sakakibara 2002). Firms in alliance blocks are often found to focus on incremental innovations in their local search strategies (specialization). In this way, block members exploit their existing capabilities by linking up with firms with similar technological profiles in their alliance block in order to benefit from deep knowledge in one particular field in which they have abundant absorptive capacity. Because block members tend to focus on technologies that are fairly similar and have an extensive knowledge base in one specific field, their local search contributes to their incremental innovations. This reinforces the block members' competence in their own technological domain and expertise (Rosenkopf and Nerkar, 2001), which leads to "deeper" knowledge and subsequent technological specialization. Technological specialization is a process of adding to the existing core technology base and further improving and deepening it in order to attain competitive advantage. Firms engage in local search for knowledge that does not conflict with existing mental models (Nelson and Winter, 1982). Despite the positive effects of specialization for companies in terms of the advancement of their current technologies, companies might be lacking the absorptive capabilities to learn from other firms that are active in different technological fields (Cohen and Levinthal, 1990). When deepening its core technology a firm will typically need to exchange highly sensitive technological knowledge. The knowledge is sensitive because it is related to core products and markets. For collaboration, trust is required to control outgoing spillovers and to decrease the risk of freeridership (Gilsing and Nooteboom, 2005). Since firms within those alliance blocks complement and build on each other's technologies, we expect that these alliance block members can reach critical mass in terms of economies of scale and scope through their technological specialization in groups. Consequently, differences in performance among competing alliance groups can be due to the nature of the technological knowledge they possess and their ability to exploit that knowledge over time (Steensma and Corley 2000). Block membership facilitates a strategy of technological specialization. Therefore alliance block members, who have a high degree of technological specialization, will benefit more from the time they are included as block members than firms that are less specialized. Therefore we hypothesize:

H3: The longer the period of block membership in combination with a high degree of technological specialization of the block member, the higher the innovative performance of block-members compared to non-alliance block members

DATA, METHOD AND VARIABLES

Our analysis refers to a group of major companies in the international microelectronics industry on which we have information regarding their partnering behavior during the period 1980-2000. The information on R&D and technology-driven alliances was obtained from the MERIT-CATI database (see Duysters and Hagedoorn (1993) for a detailed description). The total number of strategic alliances in the sample is 2,864 concerning 69 firms. Our data on R&D expenditures and revenues are available for the period from 1988 to 1997 and concern a subset of the firms for which we have alliance formation data. Taking into account a lag of one year for the explanatory variables, we restrict the period of observation from 1989 to 1997.

We focus on the microelectronics sector and its network of strategic alliances for a number of reasons. The industry has been technology-driven throughout its history, which indicates that technological positioning strategies and technology-based competition are keys to survival (Podolny and Stuart, 1995). In the microelectronics industry, one finds a large number of strategic technology alliances that play an important role in the competitive strategies of companies (see amongst others, Duysters and Hagedoorn, 1998; Gomes-Casseres, 1996; Hagedoorn, 1993; Park et al., 2002). Moreover, the microelectronics industry has shown a very high propensity to patent in the period of our study. Furthermore, the microelectronics industry is a strategically important sector, not only in terms of market size but also because its outputs are vital components in a wide range of other products. It can be considered as the driving force of technological change in virtually all sectors of the information technology industry.

The dependent variable is a count variable and takes only nonnegative integer values - i.e. the number of patents a firm successfully filed for in a particular year. In our analyses we have used a conditional fixed effects negative binomial model. An advantage of the negative binomial model is that it can account for count data that are overdispersed. [2] For this reason, we prefer the negative binomial to a Poisson estimator (Hausman, Hall and Griliches, 1984). Though the fixed effects model is less efficient than the random effects model, the fixed effects model generates consistent estimates even when unobserved and observed firm-variables are correlated

The dependent variable *innovative performance* is measured by the number of US patents successfully applied for by firms and is available for the period 1989-1997. Patents are allocated to the year the patent was applied for rather than the year it was granted to the firm, because the innovation has materialized when the company files for a patent rather than when it is granted. Despite some shortcomings, this indicator is generally considered as the most appropriate measure of innovative performance at the company level (Acs and Audretsch, 1989; Ahuja and Katila, 2001; Hagedoorn and Duysters, 2002b), especially in a single-industry high-tech sector study. Limiting the study to a single industrial sector minimizes problems related to other factors affecting patent propensity as these factors are likely to be stable within one industry (Griliches, 1990; Ahuja and Katila, 2001). [3] The microelectronics industry shows a very high propensity to patent in the period of our study. This allows us to track the innovative performance of the companies in our sample by means of their patenting activity.

The independent variable *alliance block membership* indicates whether firms are part of a specific alliance block or not. Alliance blocks are densely connected subsets of actors in a network (Knoke and Kuklinski, 1982). We operationalize alliance block membership by investigating the relative line connectivity within the group in comparison to line connectivity with firms outside the group. Line connectivity of a pair of alliance partners refers to the minimum number of lines to be removed to make sure no path exists anymore between them. Line connectivity thus indicates the extent to which a pair of alliance partners remains connected by some path, even when alliances are deleted from the alliance network.

We use 'lambda sets' to construct alliance blocks. Lambda sets compare in-group ties to out-group ties. In other words, we compare the number of alliances with partners outside the group and the number of alliances within the group (Wasserman and Faust, 1994). Lambda sets (Borgatti et al., 1990) represent a measure of cohesiveness in subgroups based on the number of alliances that should be removed in order disconnect two firms in the alliance network. [4] Relatively strong blocks are characterized by a dense set of multiple connections by its partners. The removal of specific relationships in this case does not have a large impact on the overall connectiveness of partners in the block.

The higher the clustering level, the higher the line connectivity between all pairs of alliance partners, implying the highest level of strength of ties within alliance blocks. The higher the line connectivity, the more the density of the ties with an alliance block increases. As a result, the hierarchical clustering level at which the lambda sets is constructed measures the level of embeddedness (to which we refer as 'lambda level').

To construct the '*block membership'- variable,* we chose a cut-off point in the lambda levels, which is calculated for each year in the observation period based. We chose lambda level 4 as a cut-off point: firms are connected to each other with a hierarchical clustering level of 4 or higher belong to the same alliance block. Consequently, alliance block membership is a dummy variable: firms that belong to a block (block-members) receive a value of 1 and 0 otherwise. Alternatively, we defined alliance blocks based on the clustering of Lambda sets at a clustering level of 2. Defined in this way, lambda sets are larger and less cohesive than lambda sets defined at clustering level 4. We chose level 4 as cut-off point because we found that the alliance blocks emerging at level 4 were more densely tied and better identifiable as blocks in the overall network than the alliance blocks defined at level 2. [5] To construct alliance block membership we gave firms a value of 1 when they were included in lambda sets at that clustering level 4 and 0 otherwise.

In order to estimate the relation between innovativeness and the number of years a company is member of an alliance block, we created a variable measuring the duration of block membership. For this variable, called *years in block,* we count the years in which a company is uninterruptedly present in an alliance block. We started counting the *years in block* in 1981. In our dataset this implies that a company can be engaged in an alliance block for a maximum of 16 years. The variable *technological specialization* is derived by the number of patents a firm applied for in a year in fifteen main semiconductor patent classes divided by the total number of patents it applied for per year. We expect that companies with a higher number of patent applications in microelectronics as compared to their overall patent applications (higher specialization in microelectronics), will be more innovative than firms that are less specialized in microelectronics.

To test hypothesis 3 regarding the moderating role of technological specialization on the effect of duration of block membership and innovative performance, we introduce an *interaction term.* This allows us to measure how the effect of the years a firm is pursuing an alliance *block membership* strategy is contingent on the level of technological specialization. We expect that a higher level of technological specialization positively moderates the innovative effectiveness of a certain network positioning strategy in terms of block membership or non-block membership.

We also introduced a number of control variables. First, we control for size of the firm in terms of the natural logarithm of annual revenues. [6] As we study technology partnerships, we also control for *R&D intensity*: the ratio of microelectronics-related R&D expenditures to revenues [7]. We expect a positive effect of R&D intensity on patent activity, as these research efforts will (at least partly) be transformed into patents. All independent and control variables are lagged one year.

Finally, we included two types of dummy variables. The first one indicates in which economic area the company is headquartered (Ohmae, 1985): a company can be headquartered in North America, Asia or Europe - the default is North-America. Firms from a different economic block may differ in their propensity to patent. Year dummy variables were included to capture changes over time in the propensity of companies to patent their innovations – 1989 is the default.

RESULTS

Table 1 describes the variables. Table 2 shows the descriptive statistics for all variables.

INSERT TABLE 1 ABOUT HERE

INSERT TABLE 2 ABOUT HERE

Table 3 represents the results for the fixed effects negative binomial model explaining the effect of different independent variables on the innovative performance (number of patents) of the companies. To avoid multicollinearity between block membership and years in block, we did not combine the variables in one regression (Table 3, model 1 and 2).

The first hypothesis (H1) states that alliance block members are more innovative than non-block members. The estimate in model 1 shows that block membership is indeed positively and significantly related to innovative performance. Companies in alliance blocks have on average 12% (=

exp (0.1148, $p < 0.1$) more patents than firms that are not a member of alliance blocks (see table 3, model 1).

To test hypothesis 2 we estimated the effect of the duration of block membership on innovative performance. The independent variable is the number of years a company is a block member, instead of block membership as such. According to hypothesis 2, we expect that there is a negative relation between years of block membership and innovative performance. Model 2 in Table 3 indicates that the impact on the innovativeness of the firm is negative and statistically significant (-0.0230, $p < 0.05$). Therefore, we cannot reject hypothesis 2.

INSERT TABLE 3 ABOUT HERE

We also hypothesized that a high level of technological specialization in combination with a longer duration of block membership would be beneficial for the innovative performance of an alliance block member (H3). The results for hypothesis 3 are shown in Model 2. In this model, the potential interaction between technological specialization and block based embeddedness is introduced as an interaction term.

In model 2, the coefficient for specialization is negative and highly significant (-0.5862, $p < 0.01$). In contrast, the interaction with duration has a positive and significant effect (0.1364, $p < 0.01$). This result indicates that long term membership of an alliance block pays off in case of pursuing a technology specialization.

These results imply that we find support for hypothesis 3: long term membership of alliance blocks pays off when technological specialization is high. Figure 1 illustrates the combined effect of block membership duration (number of years a firm is member of a block) and its technological specialization. Point A represents a situation where non-specialized (or technological diversified firms) have been member of a block for a long period; let us say 10 to 15 years. Firms with a highly diversified patent portfolio do not benefit from long-term membership of a particular alliance block. Point B reflects a situation in which a firm is highly specialized in a particular type of technology but stays only a few years in a block. This situation is, according to our results, also detrimental for the firm. In contrast, highly specialized firms that stay for a long time in a particular alliance block seem to profit substantially of that membership (see point C in Figure 1).

INSERT FIGURE 1 ABOUT HERE

In sum, companies with a broad technology portfolio do not profit from block membership and the effect aggravates the longer a firm stays member of that block. Highly specialized firms should avoid short term stays in an alliance block but they can increase their innovative performance considerably when they stay for a long time in a block with the same partners.

The R&D intensity variable shows a negative sign in both models. We expected a positive sign as companies with higher investment intensity in R&D should be more innovative – all else equal. The negative effect might find its roots in the inclusion of some start-ups that are outliers because they invest heavily in R&D and do not have yet commercial products on the market. The sign of the coefficient of the 'size'-variable is positive and significant as expected in both models. Finally, companies from Europe demonstrate significantly higher levels of innovative performance than their US-based and Asian competitors.

DISCUSSION AND CONCLUSION

This paper investigates the effect of alliance block membership on innovative performance. Since the academic literature has been rather inconclusive about the performance effects of multiple collaborative agreements in general and of alliance block membership in particular, this study intends to contribute both in a theoretical as well as in an empirical way to the innovation performance effects of firms in alliance networks (e.g Rowley et al. 2000; Gargiulo et al. 2000; Goerzen, 2007; Capaldo, 2007) and, more specifically, in alliance clicks . The role of firm-level ego networks and industry-level interfirm networks is increasingly better understood than the role of network substructures - like cliques or alliance blocks- that lie in between these distinct levels of analysis (Rowley et al., 2004).

Studying alliance blocks enables us to investigate some of the unexplained variance of why some networks and positions provide greater benefits to their members than to others (Pieters, 2009). Since alliance block membership can be seen as the strongest form of social embeddedness, the effect of block membership on the innovative performance of companies can therefore be considered in the light of the current debate on the advantages and disadvantages of social embeddedness (e.g. Burt, 1992; Coleman, 1988; Rowley et al., 2000).

Furthermore, prior work has paid less attention to the manner in which firm-level characteristics affect partner choice and innovative performance. Therefore, we were particularly interested in the moderating effect of the degree of technological specialization in alliance blocks. This provides a more detailed insight in the contextual issues influencing network positioning and innovative performance.

If we first make abstraction from the possible moderating effect of technological specialization, our findings indicate that a block membership strategy does indeed positively influence the innovative performance of companies. Members of cohesive subgroups develop well-embedded network ties, characterized by solid, reciprocal and trustworthy relationships (Granovetter, 1973) yielding higher innovative performance.

We expected a negative relationship between the number of years that a company is present in an alliance block and its innovative performance. This hypothesis is confirmed by the empirical results. Firms in alliance blocks tend to gradually become more restrained in taking advantage of new technological opportunities and resource niches due to being over-embedded in the network. In that case, the continuous exploitation of knowledge from the same partners leads over time to technological obsolescence (Gilsing et al., 2008) and, consequently, firms that are likely to end up in 'suboptimal equilibriums' (March, 1991:71). However, this picture changes when we consider the degree of technological specialization of block members. Our results show that although the main effect of specialization is negative (due to the low degree of absorptive capacity it creates – in particular outside blocks), technology specialization positively affects the relation between alliance block membership and innovative performance. The impact of the duration of block membership is contingent on the level of the technological specialization of the clique members. Our results indicate that long-term membership of an alliance block pays off in case of pursuing a technology specialization strategy. Long-term membership of alliance blocks is beneficial when technological specialization is high, but becomes a liability when the level of technological specialization is low. The latter case could be explained by the fact that these firms have a broad and diverse (not specialized) technology portfolio under conditions where incremental innovations based on routinization are actually more effective. Firms outside of the alliance block that engage solely in exploration suffer the costs of experimentation without gaining many of its benefits. These companies will have a hard time to individually coordinate and connect these incremental innovations and spend a substantial amount of resources on individual projects under conditions where joint, incremental innovations are more effective.

To our knowledge, this paper is a first attempt to empirically link high levels of network embeddedness (block membership vs. non-block membership) to the innovative performance of companies. Hopefully, our paper stimulates further research in investigating alliance block innovation performance. So far there is not a coherent framework to analyze either between-group or within group innovation performance.

It would be interesting to see whether the virtues of alliance block membership in terms of superior innovative performance change when the technological environment becomes turbulent and discontinuous. Recent research suggests that firms that have a greater propensity to replicate their existing ties experience inferior economic performance, particularly in environments of greater technological uncertainty (Goerzen, 2007).

Alliance formation is commonplace in many high-technology industries experiencing radical technological change, where established firms use alliances with new entrants to adapt to technological change, while new entrants benefit from the ability of established players to commercialize the new technology (Rothaermel and Boeker, 2008). Future research could specify the dynamics of entry or establishment in the network and its effect on innovative performance.

This study is limited to only one industrial sector, which enables us to systematically explore the basic questions related to network strategy and innovative performance without the methodological problems one could encounter in a multi-industry design. However, future research might provide further insight into this crucial relationship through more in-depth empirical research that covers other (high-tech) industries and deals with more contingency variables. This paper can be seen as a starting point for future empirical research aiming to improve our understanding of the complex relationship between the positioning of companies in alliance network substructures and their innovative performance.

Table 1: Description of the variables

Variable name	Variable description
Innovative performance	Count of the number of US patents successfully filed for in year t. Average over a three year period dependent variable (period 1983-2000)
Block membership	A dummy variable indicating whether firm is member of a normalized lambda set with a cutoff-point set at the hierarchical clustering level 4
Duration (Years in block)	Number of years a company is unbrokenly present in an alliance block
Specialization	The number of patents applied for in fifteen main semiconductor patent classes divided by the total amount of patents applied for per company per three year period.
Technological capital	Count of the number patents that a firm filed for during the a period three years prior to the year of observation
Firm size (ln revenues)	Natural logarithm of the total sales of the firm in t-1 (x 1000 Euro). Average over a three year period
R&D-intensity	Ratio of R&D expenditures over revenues. Average over a three year period.
Year	Dummy variable indicating a particular period (1989-1991 to 1995-1997)
Europe	Dummy variable set to one if the firm is headquartered in Europe
Asia	Dummy variable set to one if the firm is headquartered in Asia
Periods	Dummy variables indicating three year periods from 1990-1992 to 1995-1997

Table 2: Descriptive statistics and pair wise correlations

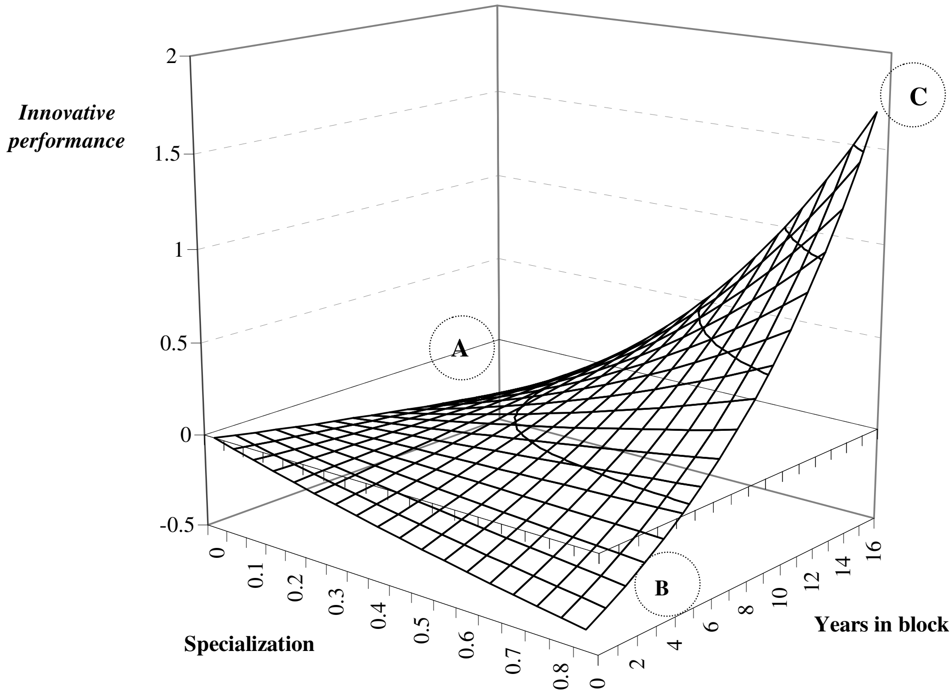
Variable	*Mean*	*s.d.*	*Min*	*Max*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*
1. Innovative performance	164.79	340.58	0	3006	1															
2. Block membership	0.49	0.500	0	1	0.3894	1														
3. Years in block	1.04	2.610	0	15	0.4102	0.7186	1													
4. R&D intensity	0.15	0.563	0.0008	9.789	-0.1241	0.1348	0.2570	1												
5. Specialization	0.39	0.309	0	1	-0.2094	-0.0090	0.0746	0.2823	1											
6. Size (ln sales)	15.36	2.069	6.7475	18.937	0.6293	0.2831	0.2789	-0.3374	-0.4943	1										
7. Europe	0.26	0.439	0	1	-0.1193	-0.0187	0.0720	-0.0763	-0.1593	0.0703	1									
8. Asia	0.24	0.424	0	1	0.2582	-0.0653	-0.1867	-0.1710	-0.1766	0.3189	-0.1972	1								
9. Year 90	0.091	0.288	0	1	-0.0671	-0.0187	-0.0547	-0.0030	-0.0700	0.0449	-0.0078	0.0190	1							
10. Year 91	0.091	0.288	0	1	-0.0907	0.0162	-0.0563	0.0459	0.0074	-0.0180	0.0047	-0.0152	-0.1235	1						
11. Year 92	0.091	0.288	0	1	-0.0706	0.1296	0.0177	-0.0045	-0.0329	-0.0063	0.0158	-0.0022	-0.1184	-0.1323	1					
12. Year 93	0.091	0.288	0	1	-0.0904	0.0606	-0.0022	0.0387	0.0132	-0.0524	0.0206	-0.0074	-0.1333	-0.1489	-0.1428	1				
13. Year 94	0.091	0.288	0	1	-0.0043	0.0131	0.0323	-0.0249	-0.0342	-0.0047	-0.0431	-0.0274	-0.1285	-0.1435	-0.1376	-0.1549	1			
14. Year 95	0.091	0.288	0	1	0.0536	-0.0387	0.0521	-0.0211	-0.0181	-0.0005	-0.0058	-0.0274	-0.1285	-0.1435	-0.1376	-0.1549	-0.1493	1		
15. Year 96	0.091	0.288	0	1	0.1076	-0.1041	0.0452	-0.0111	0.0867	0.0049	0.0101	-0.0088	-0.1210	-0.1351	-0.1296	-0.1459	-0.1405	-0.1405	1	
16. Year 97	0.091	0.288	0	1	0.1817	-0.0638	-0.0039	0.0040	0.0929	0.0113	0.0047	-0.0152	-0.1235	-0.1379	-0.1323	-0.1489	-0.1435	-0.1435	-0.1351	1

Table 3 Fixed effects estimates explaining the innovative performance of firms

Variable	*H1(model 1)*	*H2&H3 (model 2)*
Block membership	0.1148* (0.0716)	
Years in block		-0.0230** (0.0095)
(Specialization)*(Years in block)		0.1364*** (0.0357)
Specialization	-0.5848* (0.3231)	-0.5862*** (0.2257)
R&D intensity	-0.3488 (0.4557)	-0.3612 (0.4627)
Size (logarithm of revenues)	0.2865*** (0.0646)	0.4039*** (0.0477)
Europe [8]	2.6886** (1.109)	4.1408*** (1.4746)
Asia	0.4551 (0.3019)	0.4022* (0.2493)
Year 90	0.0687 (0.1422)	0.0188 (0.1094)
Year 91	-0.0007 (0.1468)	-0.1095 (0.1128)
Year 92	-0.0097 (0.1513)	-0.1521 (0.1130)
Year 93	0.0014 (0.1531)	-0.1306 (0.1129)
Year 94	0.0014 (0.1544)	0.0242 (0.1122)
Year 95	0.2795* (0.1531)	0.0716 (0.1123)
Year 96	0.4201*** (0.1541)	0.1682 (0.1146)
Year 97	0.4989*** (0.1576)	0.2405** (0.1151)
Constant	-2.492** (1.0606)	-4.2879*** (0.7642)
Loglik	-1028.16	-1476.94
Wald chi sq.	350.46***	510.01***
Number of observations	229	330
Number of firms	39	47

Notes: *Significant at the 10 % level, **Significant at the 5 % level, ***Significant at the 1 % level; I in parentheses are standard errors.

Figure 1: The combined effect of technological specialization and number of years in an alliance block



NOTES

[1] In this article we use the terms ‘alliance groups’, ‘alliance blocks’, ‘cliques’ and ‘alliance constellations’ interchangeably.

[2] In the Negative Binomial model, the variance of the dependent variable is larger than the mean, in contrast to the Poisson model, where the variance equals the mean.

[3] Also, as indicated by Hagedoorn and Cloodt (2003), in high-tech sectors, such as microelectronics, patent counts are equally well-suited for the measurement of innovative performance as other indicators such as patent citations and new product announcements.

[4] More formally one can define Lambda sets as follows: “The set of nodes *N*s, is a lambda set if any pair of nodes in the lambda set has larger line connectivity than any pair of nodes consisting of one node from within the lambda set and a second node from outside the lambda set” Borgatti, Everett and Shirey (1990).

[5] We also used a cut-off point of 2 to test for the robustness of the empirical results. The results were found to be very similar to the ones using cut-off point 4.

[6] We have chosen revenues as an indicator for firm size instead of the more frequently applied employment indicator to account for the effects of quasi-integration. Japanese companies often have fewer employees than their US and European competitors on account of the Japanese lean production methods and sophisticated customer supplier networks (Duysters and Hagedoorn, 1995).

[7] 'R&D-expenditures' would be an interesting control variable but it correlated in a very strong way (0.90) with annual sales. To avoid multicollinearity problems we chose to introduce R&D-intensity as a control variable.

[8] USA is the default.

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