Mind the gap: Balancing alliance network and technology portfolios during periods of technological uncertainty

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2009

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ABSTRACT

While clique-embeddedness is generally considered to enhance firm performance, there are also reasons to expect that under conditions of technological turbulence clique-membership is less beneficial or might even become a liability. To address this, we study the innovative performance of clique members during periods of both technological change and technological stability. We find support for the idea that companies' ability to adapt their alliance network (i.e. forming ties beyond the scope of the clique) and their ability to adapt their technology portfolios (i.e. access to novel technological knowledge) positively influences their innovative performance during technologically turbulent periods.

INTRODUCTION

Within the managerial literature it is widely accepted that innovation is most effectively undertaken as a collective process in which technology-based alliances play a critical role (See Freeman, 1991 and Pittaway et al., 2004 for reviews). As a consequence, embeddedness within a well functioning web of partners has become an essential element for a firm's technological performance (Ahuja, 2000; Powell et al., 1996). While the effectiveness of technology-based alliances is increasingly well understood from a firm-level perspective (Ahuja, 2000; Baum, Calabrese, Silverman, 2000; Hagedoorn & Schakenraad, 1994; Owen-Smith & Powell, 2004; Rothaermel & Deeds, 2004; Shan, Walker & Kogut, 1994; Stuart, 2000) and from an industry-level perspective (Rowley et al., 2000; Schilling & Phelps, 2007), there is still a shortage of studies that examines the effectiveness of technology-based alliances from a meso-level perspective, i.e. an analysis at the level of alliance cliques. Alliance cliques form intermediate network substructures that lie in-between the industry and firm level of analysis (Dorian, 1992; Rowley et al., 2004) and are characterized by strong and repeated interactions within redundant and cohesive networks. This allows clique-members to pool and transfer technological knowledge and technologies more deeply and at a higher pace (Gomes-Casseres, 1996; Lazzarini, 2007; Rowley et al., 2004). Here, the (implicit) underlying assumption is that (technological) knowledge within a group or clique is more similar than (technological) knowledge between different alliance cliques. As a consequence, alliance cliques are generally viewed as one of the most powerful sources of embeddedness and past studies have reported positive effects of clique-membership on financial and operational performance (Lazzarini, 2007; Rowley et al., 2004). However, while clique-embeddedness is generally considered to enhance performance, there are also reasons to expect that under some circumstances clique-membership is less beneficial or might even become a liability. While a certain degree of overlap in (technological) knowledge among clique members may be attractive for the exploitation of existing knowledge and technologies, it may become a liability for firms during periods of technological turbulence. Such periods of technological turbulence often have their origins beyond the clique and may contribute to the obsolescence of a firm's existing technological knowledge base (Nelson and Winter, 1982; Gilsing and Nooteboom, 2006; Ahuja et al., 2009). As a consequence, clique-membership could become a liability as knowledge and technologies inside the clique may no longer be (sufficiently) relevant to support firms to deal with the uncertainty imposed upon them during these periods. Hence, technological turbulence could represent a serious threat for clique-members when leaving it unaddressed.

A potentially effective strategic response is to explore new knowledge and technology through the formation of alliances with more distant partners. If knowledge and technologies inside alliance cliques are indeed more similar to knowledge and technology outside alliance cliques, companies may feel a need to reposition themselves beyond clique boundaries and collaborate with more distant partners. However, despite these ideas, there is still a limited understanding of these dynamic aspects of clique-embeddedness. To address this, the aim of this study is to explore three issues: (1) whether knowledge and technology are indeed more similar inside the clique than beyond clique boundaries, (2) whether the performance benefits of clique-embeddedness still apply under conditions of technological uncertainty and (3) whether collaboration beyond clique-boundaries with distant others is effective for dealing with technological turbulence. By addressing these issues, we contribute to the literature in several ways.

First, we shed some more light on the role of alliance cliques that still form an understudied phenomenon (Baum et al. 2003). Forming an intermediate network substructure between the firm and industry level, a key characteristic is that firms are fundamentally intertwined and interdependent with other firms that belong to the same clique. Although alliance cliques resemble strategic groups, which also subdivide an industry into groups of firms that compete against other groups, they have a stronger degree of coordination as they are generated by network ties - in stead of product-market and resource deployment similarities as are strategic groups (Rowley et al., 2004). Second, we consider in how far firms that collaborate with partners that are more distant from their established network structure can more easily respond to such environmental changes. Although collaboration with more distant partners comes at a price of decreasing familiarity and diminished governance benefits such as trust, this may be offset by a privileged access to unique technological knowledge and expertise that may help firms to overcome the new demands and elevated uncertainty during periods of technological turbulence. In this way, we also contribute to the literature by developing a better understanding of how this trade-off is made differently under different environmental conditions. The need for such an inquiry has been often voiced in the literature (e.g. Ahuja et al., 2009). Third, we study in how far technological turbulence affects existing network structures, which is in line with the idea that exogenous environmental changes can form an important catalyst for major changes in established network structures (Barley, 1986; Burkhardt and Brass, 1990; Glasmeier, 1991; Lambe and Spekman, 1997; Madhavan, Koka & Prescott, 1998; Soh and Roberts, 2003). In this way, we also contribute by showing how changes in alliance network structures can have important exogenous origins, which goes beyond the dominant view in the literature that has particularly emphasized the role of endogenous sources of network change (Podolny, 1994; Gulati, 1995a; 1995b; Gulati and Garguilo, 1999).

This paper is organized as follows. First, we develop theory and hypotheses regarding technological knowledge similarities within and across alliance cliques and hypotheses regarding the innovative performance of clique members during periods of both technological change and technological stability. Second, we provide a detailed description of the data, variables and methods we use to test the hypotheses. Third, we provide an overview of the most important results of our analyses using panel data covering technological activities, alliance strategies and financial data on the population of producers of ASICs (application-specific integrated circuits) for the period 1987 – 2000. In a high-tech environment like the ASIC-industry, firms are likely to establish strategic alliances among each other in order to keep up with the newest technologies (Duysters and Hagedoorn, 1996), making this an interesting industry to test our research questions. Finally, we draw conclusions and discuss the managerial implications of our main research findings.

THEORY AND HYPOTHESES

Alliance clique-membership: Knowledge similarity and innovative performance.

Alliance clique-membership is generally viewed as a powerful tool to increase innovative performance. Benefits from alliance clique-membership stem from strong and repeated interactions within a stable set of partners that enables the development of shared behavior, group norms and trust (Lazzarini, 2007; Rowley et al., 2004; Bosch-Sijtsema and Postma, 2009). These mechanisms allow alliance clique-members to pool and efficiently transfer (tacit) knowledge, which contributes to a firm's innovation performance (Uzzi, 1997; Walker et al., 1997). While prior empirical observations indicate that there indeed exists a positive relationship between clique-embeddedness and company performance (Lazzarini, 2007; Rowley et al., 2004), other insights on embeddedness indicate that not all that glitters is gold. Close and intense relationships between alliance clique-members could generate decreasing opportunities for learning and innovation within the clique as technological knowledge bases of companies may increasingly start to overlap (Hagedoorn & Frankort, 2008; Uzzi, 1997). As a consequence, the potential for finding useful new partnerships that generates new technological knowledge declines within their clique of existing partners (Duysters & Lemmens, 2003; Kenis & Knoke, 2002).

However, no prior studies have empirically tested whether knowledge and technology are indeed more similar inside an alliance clique than beyond a clique. Two underlying mechanisms may serve as an explanation why there may indeed be a positive association between joint alliance clique-membership and similarity of knowledge and technology. A first mechanism is formed by a social process of collaborative tie formation that follows a logic of preferential attachment according to which firms tend to collaborate with familiar others that are socially close in their network (Gulati, 1995a; Brass et al., 1998). A second mechanism is formed by a cognitive process of a growing mutual understanding between a firm and its alliance clique-members. Collaboration between them spurs the absorption and internalization of their mutual knowledge and technologies, which further facilitates ongoing collaboration (Mowery et al., 1996). These social and cognitive effects of collaboration contribute to a propensity of firms to persist in collaboration with alliance clique-members as familiarity and mutual understanding support firms to pool and transfer knowledge and technologies more deeply and at a higher pace

(Brass et al., 1998; Gomes-Casseres, Hagedoorn & Jaffe, 2006). As a consequence, knowledge and technologies inside the alliance clique tend to become more similar when compared to knowledge and technologies that are accessible outside the alliance clique (Brass et al., 1998). The implication that follows is that firms will want to collaborate beyond the boundaries of their alliance clique if they aspire to collaborate with partners that possess non-overlapping technological knowledge and expertise. More specifically, collaboration with partners beyond its alliance clique boundaries may provide firms with access to technological knowledge and expertise that is dissimilar from what it will find among its alliance clique-members. Overall, this leads to our first two hypotheses:

Hypothesis 1: The similarity of technological knowledge of companies embedded in the same alliance clique is larger than companies embedded in different alliance cliques.

Hypothesis 2: The similarity of technological knowledge of companies involved in new inside clique ties is larger than the similarity of technological knowledge of companies involved in new clique spanning ties.

Following the above, firms have the option to collaborate with their alliance clique-members and/or to collaborate with more distant partners beyond their alliance clique-boundaries. This raises the question regarding the relative merits of these forms of collaboration. More specifically, what are the differential effects for a firm's innovation performance of collaboration with ‘friends’ relative to collaboration with ‘strangers’? To address this question and arrive at an unequivocal prediction, we compare benefits and risks of both types of alliances.

Although collaboration with partners beyond alliance clique boundaries may provide firms with access to unique technological knowledge and expertise, it comes at a price of decreasing familiarity and diminished governance benefits such as trust and social control (Baum et al., 2005). In contrast, governance benefits form an attractive feature of collaboration with partners within alliance clique boundaries (Lazzarini, 2007; Rowley et al., 2004). Furthermore, collaboration with partners beyond alliance clique boundaries will consume more resources and managerial time compared to collaboration with alliance clique members. First, it will generally be more costly to overcome initial lack of trust and to install contractual safeguards to mitigate risks of opportunism and free-ridership (Gilsing and Nooteboom, 2006; Emden et al., 2006). Second, absorbing dissimilar knowledge and technologies will be more complex and time-consuming when compared to absorption of relatively similar technological knowledge from alliance clique-members. However, these drawbacks may be far offset by a more privileged access to novel and valuable technological knowledge and expertise that resides with more distant partners.

Overall, we expect that collaboration with both ‘friends’ and ‘strangers’ will contribute to a firm’s innovation performance. Collaboration with alliance clique-members offers efficiency of technological knowledge exchange and information transfer but will be relatively ineffective for accessing novel technological knowledge (Praest Knudsen, 2007). Collaboration with more distant partners from beyond a firm’s alliance clique offers an effective route to acquire and absorb novel technological knowledge and expertise but at the expense of efficiency and elevated governance risks. Given our focus on technology-based collaboration in a high-tech setting where considerable importance is attached to novelty (Rowley et al., 2000), we predict that collaboration with more distant partners will contribute *more* to a firm's innovation performance than collaboration with alliance clique members. This leads to our third hypothesis:

Hypothesis 3: Clique spanning ties have a stronger positive effect on innovative performance than inside clique ties.

Alliance clique-membership: technological turbulence and innovative performance

While we predict that alliance clique embeddedness carries a positive effect on performance, this relationship may not hold under all conditions. A key condition may be formed by the degree of technological turbulence. Periods of elevated technological turbulence tend to make existing knowledge and technologies become rapidly obsolete (Tushman and Anderson, 1986). Alliance clique-membership may not be beneficial in face of changing environmental conditions (Madhavan et al. 1998; Koka et al., 2006). Particularly within high-tech industries, periods of technological turbulence may lead to profound technology shifts that can threaten a firm's established knowledge and technologies and consequently hurt its competitiveness (Koka & Prescott, 2008). To address this may not be straightforward as technological turbulence makes the future difficult to predict (Beckman, Haunschild & Phillips, 2004).

Whereas stable environments emphasize the importance of exploitation of current knowledge and technologies, turbulent periods require the exploration of new knowledge and technologies (Rowley et al., 2000; Gilsing and Duysters, 2008). As a consequence, clique-embeddedness might not be beneficial for the latter purpose as the relatively high degree of similarity of knowledge and technologies inside the alliance clique offers limited room for making novel combinations that contribute to the exploration of new knowledge and technologies. So, while clique-embeddedness has a positive effect on a firms innovative performance in general (Lazzarini, 2007; Rowley et al., 2004), we expect that clique-embeddedness becomes a liability during periods of technological turbulence. Therefore we predict that the innovation performance of alliance clique-members will be negatively moderated by technological turbulence. This leads to our fourth hypothesis:

> *Hypothesis 4: Alliance clique membership has a negative effect on innovative performance during periods of technological uncertainty.*

Especially within technologically turbulent environments, companies are heavily challenged to improve their learning capabilities and knowledge and technologies (Rowley et al., 2000; Lant et al. 1992). However, the likelihood that a alliance clique-member is able to find novel knowledge and technology within its alliance clique is rather limited when compared to the potential of an alliance with a company that is not embedded within the same alliance clique. In stead, an effective way to address the uncertainties that come with technologically turbulent periods may be formed by reaching out to new, more distant partners (Burkhardt and Brass, 1990; Glasmeier, 1991; Lambe and Spekman, 1997; Soh and Roberts, 2003; Christensen , 1997; Christensen & Raynor, 2003; Faems et al., 2005).

As already mentioned, collaboration with more distant partners may initially be more costly and difficult, not only due to initial lack of trust, but also due to initial difficulties to understand one another given a higher cognitive distance compared to collaboration with alliance clique-members. As a consequence, it will take time to overcome these initial barriers before the fruits of such alliance clique-spanning collaboration can materialize. Therefore, we expect that companies that already reached out beyond alliance clique-boundaries before the advent of technologically turbulent periods will in particular be able to withstand the hazards and elevated uncertainty that characterize periods of technological turbulence. In contrast, companies that beforehand established inside clique ties will face serious difficulties during turbulent periods. Therefore, we predict that companies that have established more clique spanning ties in the past will have a superior ability to adapt to changing conditions during technologically turbulent periods when compared to companies that formed more inside clique ties. This leads to our final hypothesis:

Hypothesis 5: Clique spanning ties alleviate the negative effect of technological uncertainty on firms' innovative performance.

DATA, VARIABLES AND MODELING

Data

We constructed a panel dataset that covers the population of application specific integrated circuit (ASIC) producers over the period 1987-2000. This period captures an important period in the technological development of the ASIC-Industry. Based on industry reports (ASIC-Outlook; McClean, 1987-2000), we were able to establish a detailed list of all ASIC-producers during this period. The measures of the technological knowledge bases draw on patent data from the US Patent and Trademark Office[1]. In industries where companies operate on a global scale,

[1] The Derwent World Patent Index numbers U13-C04C; U13-C04D & U21-C01E represent all ASIC related patents during the time period 1987-2000. For our independent variables that used patents between 1982 and 1986 we performed a query within the USPTO database on 'ASIC' and related concepts/definitions such as 'gate array', 'linear array', 'FPGA', 'PLD', 'full custom', 'SPGA' and 'EPAC'(Vanhaverbeke & Noorderhaven, 2001).

such as the ASIC-industry, U.S. patents are a good proxy for companies' worldwide technological performance and technological assets (Basberg, 1983). The data on strategic technology alliances were obtained from the MERIT-CATI database on strategic technology alliances (Hagedoorn, 1993), and the ASIC-Outlook reports (McClean, 1977-2000). Financial data of ASIC producers have been gathered from different sources among which the ASIC-Outlook reports (McClean, 1987-2000) and COMPUSTAT.

Dependent Variables

This paper investigates (1) whether the technological knowledge portfolio of clique-members is more similar than those of firms belonging to different alliance cliques, (2) whether the performance benefits of clique-embeddedness still apply under conditions of technological uncertainty and (3) whether collaboration beyond alliance clique-boundaries with distant others is effective for dealing with technological turbulence. In order to accomplish this, we will make use of two separate dependent variables.

The first dependent variable considers the similarity of the technological knowledge portfolios of alliance clique-members by measuring the *technological distance* between all firms that are alliance clique-members within our observation period. Measures of technological distance have been used extensively within the alliance literature (Sampson, 2005, 2007; Rosenkopf & Almeida, 2003; Mowery, Oxley & Silverman, 1996, 1998; Nooteboom, et al., 2007). Within this research we measured technological distance based on the procedure outlined in Jaffe (1986). This method calculates technological overlap as the uncentered correlation between the respective vectors of firms' technological capital (which is measured as the cumulative patent applications in different technology classes). The values for this variable range from 0 (low technological overlap) to 1 (high technological overlap). We transformed this variable as [1 – technological overlap], resulting in a measure of technological distance, where a higher value represent a larger technological distance between two firms. In this way, a higher value of technological distance corresponds with a lower degree of technological knowledge similarity whereas a lower value of technological distance corresponds with a higher degree of technological knowledge similarity.

Our second dependent variable is a measure of innovative performance. We measured innovative performance by the number of patents that a company successfully applied for in a particular year[2]. A patent application is a signal that a company has successfully developed a technological innovation and patents have been used by many authors as an indicator of technological performance (Ahuja, 2000; Stuart, 2000; Hagedoorn & Duysters, 2002; Schilling & Phelps, 2007). We weighted patents by the citations they received as an indication of the true value of a patent assuming that more important patents receive more citations (Trajtenberg, 1990). Patent citations were collected until the end of 2007. In order to correct for right censoring of observations at the end of our observation period, we estimated the number of citations patents would receive over their life-span, based on the number of citations they received until 2007 using the simulated cumulative distribution lags developed by Hall, Jaffe & Trajtenberg (2001).

Independent Variables

[2] Patents granted by the U.S. Patent Office before the end of 2005 were included and assigned as an indicator of technological performance to the year in which they were applied for. Since the majority of patents are granted within 2 or 3 years we do not expect a right hand censoring problem.

Regarding our first hypothesis, we are interested in measuring differences in technological distance amongst companies embedded in the same alliance clique compared to companies embedded in different alliance cliques. Therefore, we included all potential dyads that could have been established between all firms reported as alliance clique-members within the observation period. This resulted in an unbalanced panel set of 60.733 pairs of firms for this time period, but this set includes a lot of firms that did not apply for patents. We restricted our analysis to firm-pairs where both partners have at least one patent as including observations with zero observations is both methodological as conceptual problematic (Gomes-Casseres, Hagedoorn & Jaffe, 2006). Next, we excluded all firms that did not have at least one ASIC related patent since we could not determine the configuration of their technological knowledge bases without relying on patents. Within approximately three quarters of all pairs of firms we did not observe a patent. After elimination, 14.166 pairs of firms are left for which we were able to assess the technological distances. Last, we coded each pair of firm as being embedded in the same alliance clique (3.230 dyad-year observations) and as being embedded in different alliance cliques (11.936 dyad-year observations).

For our second hypothesis we included all newly established alliances in a given year. Within the period 1987 - 2000 we found 521 alliances established within the ASIC-Industry. To test this hypothesis, we measured differences in technological distance amongst inside clique ties and clique spanning ties and therefore we included only ties that fell into these categories which resulted in 416 pairs of firms. Next, we excluded all firms that did not have at least one ASIC related patent. Once these firms' pairs were eliminated we are left with a total of 124 ties of which we were able to assess the technological distances amongst them. Last, we coded these ties as being inside clique ties (63 dyad-year observations) and as being clique spanning ties (61 dyad-year observations).

For the fourth and fifth hypothesis we measured the amount of technological change within a certain year. Measures of technological change have been used in prior studies (Madhavan et al., 1998; Koka & Prescott, 2008; Van de Vrande et al., 2009). We followed Hannan & Freeman, (1989) and Delecroix & Swaminathan (1991) to measure change as the amplitude of change within the industry of interest. This measure results in an indication as to which the technological environment within the ASIC-industry was unpredictable for individual ASIC firms within a given year. In order to calculate this measure we counted the number of patents within a given year t and measured the relative deviation from the average number of industry patents in t -1 to t – 3.

We use social network analysis to measure whether companies belong to the same or different alliance cliques. In this way, we can measure whether a new alliance is an inside clique tie or a clique spanning tie. In line with prior research on alliance cliques (Rowley et al., 2005), we used the N-Clan procedure implemented in UCINET (Borgatti, Everett & Freeman, 2002) to detect relevant alliance cliques. The N-Clan procedure allows firms to be embedded in more than one alliance clique and detects alliance cliques based on a predefined maximum distance between all firm in the alliance clique and a predefined minimal size of the alliance clique. By using a maximum distance of 2 we assured that firms in the same alliance clique were either connected by a direct tie or by an indirect tie. By using a minimal group size of 5 members we assured that alliance cliques had a significant size to detect variations across alliance cliques in terms of their internal and external linkages. For each observation year we (re)calculated our alliance clique measures, hence this method allows alliance clique composition to vary over time.

We build our hypothesis on prior clique spanning ties around the strategic intentions of a firm past alliance behaviour over the last 5 years prior to the observation year. Under pressure of changes external to the alliance network and dynamics internal to the existing network, firms establish new ties and dissolve, strengthen or weaken existing ones (Koka, Madhavan & Prescott 2006). The strategic intentions of clique-members new tie formation have been classified into "*inside clique ties*", "*outside clique ties with peripheral network members*" and "*clique spanning ties*" (i.e. "outside clique ties with members of other cliques"). If a new tie formed in year *t* bridges two distinct cliques in the alliance network of *t*-1 a tie can be considered as a clique spanning tie. After categorizing all these ties, the number of clique spanning ties has been measured by counting the number of clique spanning ties that a firm initiated 5 years prior to the observation year (*t*-1 to *t*-5).

Control Variables

First, we included four organizational variables. As our first organizational variable, we included technological capital to control for the total size of a firm's technological knowledge base. This variable was created by adding up all ASIC-related patents that a firm received during the five years prior to the year of observation. A moving window of 5 years is considered as an appropriate time frame for assessing the technological impact in high tech industries (Podolny & Stuart, 1995; Henderson & Cockburn, 1996). This variable also allows to control for unobserved heterogeneity at the firm level.

The second organizational variable relates to the size of the firm. Large firms have a broader and more diversified network of alliances (Hagedoorn & Duijsters, 2002) and are considered as dominant firms, not only within the alliance clique but also in the overall alliance network. Due to their size, large firms are more likely to profit from economies of scale and scope and thereby they have a higher potential to strengthen their technological performance over time. We calculated this variable based on the natural logarithm of a firm's annual sales. The third organizational variable relates to the absorptive capacity of the firm (Cohen and Levinthal, 1990). Firms that invest more in R&D have broader possibilities to experiment and explore new kinds of technologies (Grimpe, 2007). We calculated this variable based on the R&D to sales ratio of each firm. A fourth organizational variable was included to control for a potential bias as some large companies produce ASIC's only for their internal needs (captivity). These captive producers are a small minority of ASIC-producing companies but they are nonetheless important in terms of technological capabilities and therefore play an important role in the technological development of the ASIC industry (e.g. IBM and Texas Instruments).

Furthermore, we include three types of dummy variables to control for different types of contingencies. First, industry dummy variables were included to indicate the industry segment to which an ASIC-producer belongs (gate arrays (GA), standard cells (SC) and programmable logic devices (PLD)). Firms can be involved in the production of only one segment or in more segments of the ASIC industry at the same time. Segments are important in the sense that firms in each segment face different technological challenges, competitors and competitive or technological dynamics. The second dummy variable indicates in which economic region the company is headquartered (Asia, North America or Europe), where the default is North America (Ohmae, 1985). Finally, year dummy variables were included to capture changes over time in the propensity of firms to patent their inventions. Table 1 provides an overview of all the variables included in the empirical analysis.

Insert Table 1 about here

RESULTS

In table 2 we present the descriptive statistics and the correlation matrix for the different variables.

Insert Table 2 about here

Our hypotheses 1 and 2 predicted differences in technological distance between alliance clique-members and non-alliance clique-members and between clique spanning ties and inside clique ties. Hypothesis 1 states that the similarity of technological knowledge of companies embedded in the same alliance clique is larger than companies embedded in different alliance cliques. The technological distance measure takes a value between 0 and 1, where a higher value of technological distance corresponds with a lower degree of technological knowledge similarity whereas a lower value of technological distance corresponds with a higher degree of technological knowledge similarity. Our empirical results show that the mean technological distance between members of the same alliance clique (mean = 0.57)[3] is smaller than the

[3] Standard deviation : 0.25 and 3.230 dyad-year observations.

technological distance of companies embedded in different alliance cliques (mean = 0.63)[4]. We used a t-test in order to test whether these means are statistically different from each other. The results of the t-test (p=<0.05**) are in support of hypothesis 1, indicating that the technological knowledge bases of companies embedded within the same alliance cliques are more similar than technological knowledge bases of companies embedded in different alliance cliques.

Hypothesis 2 predicts that the similarity of technological knowledge of companies involved in new inside clique ties is larger than the similarity of technological knowledge of companies involved in new clique spanning ties. Our empirical results indicate that the technological distance of an inside clique tie (mean = 0.53)[5] is smaller than the technological distance of a clique spanning ties (mean = 0.62)[6]. The results of the t-test (p=<0.001***) support hypothesis 2 predicting that similarity of technological knowledge of companies involved in new inside clique ties is larger when compared to similarity of technological knowledge in new clique spanning ties, suggesting that the formation of a clique spanning ties connects a firms to technological knowledge that is more novel to this firm than the formation of an inside clique tie.

The dependent variable in hypotheses 3-5, weighted patent counts, is a count variable. Because our data show evidence of overdispersion, a negative binomial regression model is an appropriate estimation method (Cameron & Trivedi, 1998). To determine the choice between a random-effect and fixed-effect model we conducted a Hausman test (1978). The results of the Hausman test indicate that the firm specific random effects and the regressors correlate with each other, indicating that random effects negative binomial model is not a consistent estimator. As a result, we use a fixed effects model for the models in the tables 3 and 4. Table 4 shows the results of the fixed effects negative binomial regression analyses for the 517 firm-year

[4] Standard deviation : 0.34 and 11.936 dyad-year observations.
[5] Standard deviation : 0.28 and 63 dyad-year observations.
[6] Standard deviation : 0.30 and 61 dyad-year observations.

observations in the sample. Because these hypotheses used different samples we estimated two different models. The results of hypotheses 3 and 5 are reported in table 4, the results of hypotheses 4 are reported in table 3. The regressions in Table 3 are based on 848 firm-year observations whereas Table 4 only counts 517 firm-year observations. This difference is explained by the fact that hypothesis 4 measures the innovative performance of all firms in the sample (clique members vs. non-clique members), whereas hypotheses 3 and 5 measure the innovative performance of alliance clique members only (clique spanning ties vs. inside clique ties). Within both tables we present baseline models (model 1 and model 5), including only the variables controlling for companies' technological distance, technological capital, size, R&D intensity and captivity- sector, region and trend effects.

Insert Table 3 about here

Insert Table 4 about here

Models 6-7 in table 4 report the results of hypothesis 3 focusing on the effects of inside clique ties and clique spanning ties on innovative performance. These models add in a stepwise way the effects of inside clique ties (model 6) and clique spanning ties (model 7). We find that both the formation of inside clique ties and the formation of clique spanning ties have a positive effect on firms' innovative performance. We used a t-test in order to test whether these means are statistically different from each other. The results of the t-test (p=<0.05**)[7] are in support of hypothesis 3, indicating that clique spanning ties have a stronger positive effect on innovative performance than inside clique ties.

Models 2-4 in table 3 report the results of the test whether the effect of alliance clique membership on innovative performance is smaller under periods of technological turbulence compared to periods of technological stability. We entered the effects in a stepwise way introducing subsequently technological turbulence (model 2), alliance clique membership (model 3) and the interaction of both variables (model 4). The results in model (4) do not support hypothesis 4: since the interaction term is not statistically significant alliance clique-membership is beneficial for innovating firms both in technologically stable as well as turbulent periods. Clique membership seems to be beneficial for clique members in general independent of the turbulence in the environment. However, it is interesting to look at individual difference between clique members and check whether their alliances and technological capital helps them in overcoming turbulent periods better than the other clique members. Models 8-10 in table 4 report the results for the tests of hypothesis 5 which looks at the effect of firms' past clique spanning ties and inside clique ties on innovative performance during periods of technological uncertainty. Contrary to the results for all ASIC-producers (model 2, table 3), technological turbulence does have a slightly negative effect on the innovative performance of alliance clique-members (model 8, table 4). This result is interesting in itself as it indicates that the innovative performance of non-alliance clique members is responsible for finding a non-significant estimator of technological turbulence for the overall population. As model 9 indicates we find support for hypothesis 5, indicating that the establishment of past clique spanning ties has a positive effect on the innovative performance of alliance clique-members during periods of technological turbulence[8]. Alliance clique-members that established more past clique spanning ties have better access to novel technological knowledge which may help them to address the uncertainties and needs that come with these turbulent periods. Combining the results of model 4 in table 3 and model 9 in table 4, we come to the conclusion that in general being member of an alliance clique is advantageous for innovating companies, but not all members benefit equally since the effect is only positive for those companies that have previously established clique spanning ties.

DISCUSSION AND CONCLUSIONS

Alliance cliques are generally viewed as one of the most powerful sources of embeddedness since clique-embeddedness enables efficient pooling and transfer of knowledge and technologies amongst a wider set of partners (Gomes-Casseres, 1996 Lazzarini, 2007; Rowley et al., 2004). As our findings indicate, technological knowledge within an alliance clique is more homogenous than between different alliance cliques. The similarity of knowledge and technology within the alliance clique can be considered as the result of the interaction process among alliance clique-members that internalize their partner's knowledge and technologies, which causes them to become more alike over time (Mowery et al., 1996; Brass et al., 1998; Nooteboom, 2000; Wuyts et al., 2005). While clique-embeddedness is generally considered to enhance performance (Lazzarini, 2007; Rowley et al., 2004), there are also reasons to expect that under certain circumstances clique-embeddedness is less beneficial or might even become a liability. Such conditions can be formed by technological turbulence that tends to make existing technological knowledge bases obsolete and may render clique-embeddedness ineffective. As a consequence,

[8] We also calculated the interaction effect of inside clique ties under periods of technological turbulence. This model indicates that only the main effects of past inside clique ties (positive) and technological turbulence (negative) influence the innovative performance of companies in the ASIC-industry. Hence, having established more past inside clique ties does not have an effect on the innovative performance of alliance clique-member during technologically turbulent periods.

whereas overlap in technological knowledge among alliance clique members may be attractive for the exploitation of existing knowledge and technologies, it may become a liability for firms during periods of technological turbulence. The relative homogeneity of knowledge and technologies inside the alliance clique tends to make alliance clique-members insufficiently equipped to engage in the exploration of new knowledge and technologies (Burt, 2000; Rowley et al., 2000). Therefore, alliance clique-members may have a clear incentive to establish clique spanning ties as this connects them to companies who possess technological knowledge that is (far) more novel relative to its current technological knowledge base than knowledge obtained through the formation of an inside clique tie. In line with this, we found that under conditions of technological turbulence the formation of clique spanning ties strongly enhances innovative performance.[9]

The formation of clique spanning ties allows firms to absorb knowledge and technologies that could potentially help them in addressing new technologies that characterize periods of technological turbulence. In line with this, we expected that alliance clique-membership might become ineffective or even a liability during these periods. Turbulent environments require a network position that facilitates exploration of new technological knowledge, while stable environments emphasize the importance of network positions that enable exploitation of current knowledge (Burt, 2000; Rowley et al., 2000). We did not find support for the notion that alliance clique-membership becomes a liability during periods of technological change. Rather we found that alliance clique-membership as such does not have any effect on firm's innovative performance during technologically turbulent periods. However, we also found that clique members that form clique spanning ties prior to technologically turbulent periods can improve their innovative performance during those periods to a considerable extent.

[9] Whereas the formation of additional inside clique ties appears to be ineffective.

The current study is explorative and has several limitations and directions for future research. The current study is limited to a single industry and, therefore, we should be cautious extrapolating these results towards other industries. Next, this study was limited to a technique that detected overlapping alliance cliques. A firm's position inside the alliance clique as well as its past alliance behavior is therefore dependent on the ability of this overlapping procedure to precisely ascribe the right processes towards the focal firms and their alliances. "The clique is a theoretical construct with a potentially high value for developing theory on inter-firm networks, but their empirical value is determined by whether they are also real social actors with empirically traceable effects" (Baum et al., 2003, p.719). Alliance cliques are however gaining momentum in the managerial literature with promising potential to link multiple levels of analysis in the network literature (Baum et al., 2003; Lazzarini, 2007; Padula, 2008; Rosenkopf & Padula, 2008; Rowley et al., 2004; 2005). Our results indicate that alliance clique-membership does enhance a firm's innovative performance, but that not all that glitters is gold for all members of the alliance clique. Especially during technologically turbulent periods, not all alliance clique-members are able to equally profit from their alliance clique-embeddedness. Alliance clique-members that established more alliances that link them to knowledge and technologies of other alliance cliques are more innovative than alliance clique-members lacking this type of alliances.

Overall we contribute to the literature in a number of ways. Our findings demonstrate that there is a limit to the dominant view in the literature stressing the role of endogenous network dynamics that lead to durable and self-reproducing network positions (Baum et al., 2003; Gulati, 1995a, 1995b; Gulati & Garguilo, 1999). This process of 'structural differentiation' refers to a pattern of incremental network change in which firms increasingly have repeated ties among already well-embedded firms (Baum et al., 2003; Gulati & Garguilo, 1999; Powell et al., 2005). Here, we have demonstrated that firms also engage in the formation of ties with more distant partners beyond this set of repeatedly cooperating firms (Baum et al., 2003; Rosenkopf & Padula, 2008). This is especially useful in turbulent periods of technological change that renders alliance clique-membership and collaboration with existing alliance clique-partners ineffective, as opposed to collaboration with more distant others. Whereas collaboration with more distant partners comes at a price of decreasing familiarity and governance benefits such as trust, it offers firms access to more unique technological knowledge that may help them to overcome the new demands and elevated uncertainty that are imposed upon them during periods of technological turbulence. In this way, our study suggests that the process of 'structural differentiation' especially carries positive performance effects as long as there is environmental stability but may become ineffective in case of changing environmental conditions.

An important implication that follows is that the influential notion of 'similarity breeds attraction' (Gulati 1995a) is beneficial as long as external conditions remain relatively stable. However, environmental turbulence creates a need for a new kind of collaborative behavior where 'dissimilarity breeds attraction' as it is under changing conditions that collaboration with more distant others especially contributes to boosting innovative performance. In this way, we also contribute to the literature on social capital as our findings suggest that Burt's structural hole argument, emphasizing the value of a bridging strategy across non-redundant partners, may especially pay off when external conditions change.

Overall, these implications for some key ideas in the literature - structural differentiation (Gulati and Garguilo, 1999) and brokerage (Burt, 1992) - suggest that no matter how useful a social structural perspective is, its prescriptive value is more liable to be a function of the environmental context than has been assumed in the literature until now. In this way, alliance cliques as an intermediate level of analysis between the industry-level and the firm level in combination with the role of technological turbulence have shown to be relevant contingencies to better understand the boundary conditions of common wisdom in the broad literature on strategic alliances and network embeddedness.

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TABLE 1
Definitions of dependent and independent variables

Variable name	*Variable description*	*H*
Innovative performance	Count variable indicating the number of successful patent applications, weighted by the number of citations they receive.	
Technological Turbulence	Amplitude of change as the relative growth of the number of patents between year *t -1* over the mean of the preceding 3 years *t-2 to t-4*	
Clique membership	Dichotomized variable (0/1) indicating if a firm is a alliance clique member in alliance network *(t-1 to t-5)*	
Past inside clique ties	Prior ties that a firm formed inside its own alliance clique *(t1 to t5)*	
Past clique spanning ties	Prior ties that a firm formed that brokered two different alliance cliques *(t1 to t5)*	
Technological Distance	Technological distance between the focal firm and its partners based on their patent portfolios	
Technological Capital	Count variable indicating the number of successful patent applications in *(t-1 to t-5)*	
Firm Size	Total overall sales of the focal firm/1000 *(t-1)*	
Firm R&D to sales ratio	Firm total R&D expenditures / Firm overall sales *(t-1)*	
Firm is Captive producer	Dummy variable denoting that the firm is not selling products on the ASIC-market	
Firm is SC-Producer	Dummy variable denoting that the firm is producing only Standard Cells	
Firm is PLD-Producer	Dummy variable denoting that the firm is producing only PLDs	
Firm is GA&SC-Producer	Dummy variable denoting that the firm is producing only Gate Arrays and Standard Cells	
Firm is GA&PLD-Producer	Dummy variable denoting that the firm is producing only Gate Arrays and PLDs	
Firm is SC&PLD-Producer	Dummy variable denoting that the firm is producing only Standard Cells and PLDs	
Firm is GA&SC&PLD-Producer	Dummy variable denoting that the firm is producing Gate Arrays and Standard Cells and PLDs	
Firm is European	Dummy variable denoting that the firm is headquartered in Europe	
Firm is Asian	Dummy variable denoting that the firm is headquartered in Asia	
Trend	Variable denoting the year of observation	

TABLE 2
Descriptive statistics and correlation matrix

	Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10
All firms (848 obs.)															
1	Innovative performance	97.85	311.88	0	3791.54	1.00									
2	Technological Turbulence	0.36	0.30	0.04	1	-0.04	1.00								
3	Alliance clique-membership	0.66	0.48	0	1	0.16	-0.03	1.00							
4	Technological Distance	0.52	0.22	0.03	1	-0.11	-0.01	-0.06	1.00						
5	Technological Capital	10.93	24.06	0	307	0.76	-0.05	0.22	-0.14	1.00					
6	Firm Size	1.42	2.21	0	16.41	-0.05	-0.01	0.20	-0.05	0.06	1.00				
7	Firm R&D to sales ratio	0.11	0.08	0	0.87	0.07	0.03	0.01	-0.10	0.02	-0.35	1.00			
8	Firm is Captive producer	0.17	0.37	0	1	-0.11	0.02	-0.03	0.02	-0.13	0.19	-0.14	1.00		
9	Firm is European	0.14	0.34	0	1	-0.09	0.01	0.10	0.00	-0.11	0.08	-0.03	0.09	1.00	
10	Firm is Asian	0.28	0.45	0	1	-0.12	-0.03	0.01	0.09	-0.03	0.19	-0.39	-0.16	-0.25	1.00

	Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11
Clique-members (517 obs.)																
1	Innovative performance	144.06	373.54	0	3791.54	1.00										
2	Technological Turbulence	0.35	0.29	0.04	1	-0.04	1.00									
3	Past inside clique ties	1.47	2.01	0	9	-0.05	0.02	1.00								
4	Past clique spanning ties	1.21	1.23	0	8	0.08	-0.01	0.40	1.00							
5	Technological Distance	0.49	0.24	0.03	1	-0.11	0.02	-0.11	-0.09	1.00						
6	Technological Capital	15.62	27.21	0	307	0.73	-0.05	0.02	0.21	-0.14	1.00					
7	Firm Size	1.80	2.43	0.00	16.41	-0.11	-0.01	0.14	0.16	-0.00	0.00	1.00				
8	Firm R&D to sales ratio	0.11	0.07	0.01	0.67	0.07	-0.06	-0.08	-0.07	-0.12	0.01	-0.43	1.00			
9	Firm is Captive producer	0.16	0.37	0	1	-0.13	0.03	-0.10	-0.12	0.06	-0.15	0.19	-0.17	1.00		
10	Firm is European	0.17	0.38	0	1	-0.14	0.00	0.41	0.02	0.06	-0.17	0.04	-0.03	0.15	1.00	
11	Firm is Asian	0.27	0.45	0	1	-0.14	-0.02	-0.16	-0.10	0.12	-0.05	0.23	-0.42	-0.13	-0.28	1.00

TABLE 3

Fixed effects panel estimation results for Innovative performance

	(1)	*(2)*	*(3)*	*(4)*
Turbulence		-0.23 (0.15)	-0.23 (0.15)	-0.08 (0.34)
Clique-Member			0.70 (0.14)***	0.76 (0.18)***
Clique-Member*Turbulence				-0.16 (0.33)
Technological Distance	-1.45 (0.24)***	-1.45 (0.24)***	-1.33 (0.23)***	-1.32 (0.23)***
Technological Capital	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***
Firm Size	0.13 (0.03)***	0.13 (0.03)***	0.11 (0.03)***	0.10 (0.03)***
R&D Intensity	-0.38 (0.79)	-0.31 (0.81)	-0.34 (0.87)	-0.41 (0.88)
Captive Producer	-0.14 (0.20)	-0.15 (0.20)	-0.15 (0.20)	-0.15 (0.20)
GA-Producer	-1.50 (0.31)***	-1.49 (0.31)***	-1.32 (0.31)***	-1.32 (0.31)***
SC-Producer	-1.68 (0.26)***	-1.70 (0.26)***	-1.61 (0.26)***	-1.62 (0.26)***
GA & SC-Producer	-0.82 (0.22)***	-0.83 (0.22)***	-0.88 (0.22)***	-0.88 (0.22)***
SC & PLD-Producer	0.20 (0.46)	0.18 (0.46)	0.01 (0.46)	0.00 (0.46)
GA & PLD-Producer	0.62 (0.28)**	0.63 (0.27)**	0.55 (0.27)**	0.55 (0.27)**
GA-SC & PLD-Producer	-0.42 (0.23)*	-0.42 (0.23)*	-0.47 (0.23)**	-0.48 (0.23)**
Firm is European	-0.32 (0.21)	-0.32 (0.21)	-0.37 (0.21)*	-0.37 (0.21)*
Firm is Asian	0.17 (0.17)	0.16 (0.17)	0.26 (0.17)	0.25 (0.17)
Constant and year variables	Included	Included	Included	Included
Observations (firms)	848 (71)	848 (71)	848 (71)	848 (71)
Log Likelihood	2587,67	2586,49	2571,54	2571,42
Lr-test		n.s.	***	n.s.

TABLE 4

Fixed effects panel estimation results for Innovative performance

	(5)	*(6)*	*(7)*	*(8)*	*(9)*
Inside Ties		0.13 (0.04)***			
Clique Spanning Ties			0.26 (0.04)***		0.28 (0.04)***
Turbulence				-0.30 (0.15)*	-0.56 (0.22)***
Clique Spanning Ties * Turbulence					0.07 (0.03)**
Technological Distance	-1.01 (0.26)***	-1.03 (0.26)***	-1.02 (0.26)***	-0.97 (0.26)***	-0.99 (0.26)***
Technological Capital	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***
Firm Size	0.08 (0.03)**	0.05 (0.03)*	0.04 (0.03)	0.08 (0.03)**	0.05 (0.03)
R&D Intensity	-0.77 (1.25)	-0.82 (1.26)	-0.72 (1.23)	-0.91 (1.25)	-0.85 (1.24)
Captive Producer	-0.08 (0.24)	-0.04 (0.24)	0.17 (0.23)	-0.09 (0.24)	0.13 (0.23)
GA-Producer	-1.23 (0.48)**	-1.19 (0.48)**	-1.32 (0.48)***	-1.23 (0.48)**	-1.29 (0.48)***
SC-Producer	-1.40 (0.31)***	-1.43 (0.31)***	-1.67 (0.31)***	-1.43 (0.31)***	-1.67 (0.31)***
GA & SC-Producer	-0.79 (0.24)***	-0.87 (0.24)***	-1.00 (0.24)***	-0.83 (0.24)***	-1.04 (0.24)***
SC & PLD-Producer	-0.10 (0.46)	-0.64 (0.49)	-0.18 (0.44)	-0.13 (0.46)	-0.27 (0.44)
GA & PLD-Producer	0.46 (0.29)	0.48 (0.28)*	0.52 (0.28)*	0.45 (0.29)	0.52 (0.27)*
GA-SC & PLD-Producer	-0.30 (0.25)	-0.58 (0.26)**	-0.49 (0.25)*	-0.33 (0.25)	-0.55 (0.25)**
Firm is European	-0.64 (0.23)***	-0.92 (0.24)***	-0.65 (0.23)***	-0.65 (0.23)***	-0.67 (0.23)***
Firm is Asian	0.21 (0.21)	0.37 (0.21)*	0.40 (0.21)*	0.18 (0.21)	0.34 (0.21)
Constant and year variables	Included	Included	Included	Included	Included
Observations (firms)	517 (51)	517 (51)	517 (51)	517 (51)	517 (51)
Log Likelihood	2022,83	2016,22	2003,06	2021,16	1999,26
Lr-test		***	***	n.s.	***