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DO ALLIANCE CLIQUES MATTER?

Explaining innovative performance and alliance network dynamics through alliance clique membership and technological capabilities

MICHIEL PIETERS

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1.1 Introduction.

Under the condition of fast technological change, networks, not firms, have become the actual operating unit. (...) A new organizational form has emerged as characteristic of the informational, global economy: "the network enterprise" (Castells, 1996, p-187).

The rise of the so-called network society *(Castells, 1996)* has caused managers and researchers alike to adapt their traditional view on the firm. Under the condition of fast technological change, companies cannot afford a closed innovation model anymore and increasingly choose to balance internal and external sources of knowledge and technology in their innovation process *(Chesbrough, 2003; Chesbrough, Vanhaverbeke & West, 2006).* The increasing dependency on external sourcing of knowledge and technology is a significant break with the past where large corporations were almost self-contained and self-sufficient in this sense *(Pfeffer & Salancik, 1978).* Especially in high-tech industries, companies transformed from autonomous and distinct units of action to organizations embedded within networks that blur hierarchical boundaries *(Baum & Ingram, 2002; Granovetter, 1994; Gulati & Garguilo, 1999; Powell & Smith-Doerr, 1994).* Consequently, embeddedness within a well functioning web of partners has become an essential element for a firm's technological and/or economical performance.

This dissertation focuses on technology-based alliances as a governance mode for external sourcing of knowledge and technology *(Ahuja, 2000a; Hagedoorn & Duysters, 2002; Katila & Mang, 2003; Powell, 1998; Rosenkopf & Almeida, 2003; Schilling & Phelps, 2007; Stuart, 1998).* During the past decades, the use of technology-based alliances has grown at an impressive rate *(Hagedoorn, 1996, 2002)*, and there is an abundance of empirical evidence that underlines the importance of technology-based alliance for a firm's innovative performance *(See Freeman, 1991; Meeus, Oerlemans & Kenis, 2008; Pittaway et al., 2004 for reviews).* While these papers confirm the extensive knowledge on technology-based alliances as a governance mode for external sourcing of knowledge and technology, many questions still remain unanswered. For example, the dynamic nature of alliances and alliance networks has only recently received some attention, although most scholars agree that a longitudinal view on alliance networks is required to fully understand how companies can manage the process of external sourcing of knowledge and technology effectively *(Nohria, 1992; Rowley & Baum, 2008).* The current study is part of the research theme on how alliance networks emerge and evolve over time and how these network dynamics influence the innovative performance of the embedded firms. The contribution of this dissertation to this literature is twofold. First, it extends the current knowledge about the effect of dynamics in technology-based alliance networks on innovative performance by investigating the opportunities and threats stemming from clique-embeddedness. Second, it extends the current knowledge about the exogenous and endogenous drivers of network dynamics itself by incorporating clique topology – i.e. local clustering and shortcuts – into the existing theories of network evolution. The goal of this introductory chapter is to give a description of the literature that this dissertation will contribute to and to clarify the research problems that will be addressed. This chapter concludes with a short overview of the lay-out of this dissertation.

1.2 Alliance networks and innovation.

The goal of this section is to provide a clear overview about the current insights into how technology-based alliance networks affect innovative performance, and to describe how investigating the opportunities and threats stemming from clique-embeddedness contributes to this field of knowledge. Over the years, many reviews and essays have provided an excellent overview of the causes and consequences of alliances and alliance networks in general *(Borgatti & Foster, 2003; Brass et al., 2004; Galaskiewicz 1985, 2007; Gulati, 1998; Gulati, Nohria & Zaheer, 2000; Oliver & Ebers, 1998; Provan, Fish & Sydow, 2007; Rowley & Baum, 2008; Salancik, 1995*) and of technology-based alliances and innovative performance in particular (*See Freeman, 1991; Meeus, Oerlemans & Kenis, 2008; Pittaway et al., 2004 for reviews*). Currently it is widely accepted that innovation is most effectively undertaken as a collective process in which technology-based alliances play a critical role. Building effective technology-based alliance networks has become an important firm-capability as technology-based alliances can only stimulate innovative performance when companies are able to exchange knowledge and technologies. Yet, while technology-based alliances should allow all embedded firms to enhance its innovative performance, empirical evidence also indicates that not all firms are able to enhance its innovative performance equally *(e.g. Ahuja, 2000a; Hite & Hesterly, 2001; McEvely & Zaheer, 1999; Garguilo & Benassi, 2000; Rowley, Behrens & Krackhardt, 2000).*

The effectiveness of a firm's participation in technology-based alliances has been ascribed to two underlying mechanisms: the opportunity to access valuable knowledge and technology flows and the opportunity to control the knowledge and technologies flowing in the alliance network *(Coleman, 1988; Burt, 1992).* In order to analyze these two mechanisms, a complete picture of the alliance network is needed since firms' position in the alliance network and the type of alliances it maintains defines its access to, and control over, those opportunities *(Uzzi, 1996).* Recently, researchers have begun to identify some of these factors that mediate the effect of technology-bases alliance on innovative performance by explaining why some networks and positions provide greater benefit to their members than to others[1] *(Gulati, 1998).* Improving our knowledge and understanding about these factors is important as this allows companies to manage the process of external sourcing of knowledge and technology more effectively. From a network perspective, the effectiveness of firms' participation in technology-based alliances is unevenly distributed because companies show significant variations in terms of (*1*) the strength of their relations, (*2*) the structure of their ego-network, (*3*) their positions in the overall network and (*4*) the configuration of the overall alliance network in which it is embedded.

Relational embeddedness. Relational embeddedness highlights the effects of the strength of the alliance between two cooperating companies *(Granovetter, 1973; Gulati & Garguilo, 1999).* Strong ties facilitate the development of trust as these stable relationships provide firms with a reliable indication about the behavior and reliability of each other. These conditions facilitate efficient and effective transfer of tacit and complex knowledge and technologies between these partners, which is a positive contributor to the innovative performance of these firms *(Uzzi, 1996).* However, there is still an ongoing debate about the influence of relational embeddedness on innovation *(Gilsing & Nooteboom, 2005)* as other scholars have argued that weak ties enable firms to explore novel sources of knowledge and technology *(Granovetter, 1973).* Weak ties require less managerial attention and are therefore less costly which could make weak ties more efficient contributor to innovative performance as compared to strong ties. Most empirical studies find positive effects of the strength of an alliance on innovative performance *(Zollo, Reuer & Singh, 2002; Capaldo, 2007).* However, other empirical findings indicate that weak ties are indeed beneficial for exploration, especially in uncertain technological developments, and that strong ties are beneficial for exploitation, especially in industries with low technological uncertainties *(Rowley, Beehrens & Krackhardt, 2000; Dyer & Nobeoka, 2000).*

Structural embeddedness. Structural embeddedness moves beyond the dyad level of analysis and incorporates the local structure of relations around a company and the tendency of these relations to cooperate amongst each other *(Granovetter, 1992).* Within this debate it has been argued that embeddedness in a highly redundant and dense ego-network is beneficial for the transfer of (tacit) knowledge and technologies because coordination and communication is improved trough repeated exchange with stable partners *(Coleman, 1988)*. Furthermore, these cohesive networks facilitate the development of trust which decreases the likelihood of opportunistic behavior *(Williamson, 1985).* Sharing of knowledge and technologies amongst a wide range of contacts allows for a deeper understanding of knowledge and technologies and increases the coherence of the knowledge and technologies under study. However, highly

[1] After controlling for other factors that may influence innovative performance

redundant and dense ego-networks decrease the opportunity that firms are able to control the knowledge flowing in the alliance network *(Burt, 1988).* Firms within a non-redundant and less dense network benefit from the opportunity to bridge disconnected parts in its ego-network. The literature on cohesive networks vs. sparse networks in relation to innovative performance is rather inconclusive *(Ahuja, 2000a; Hite & Hesterly, 2001; McEvely & Zaheer, 1999; Garguilo & Benassi, 2000; Rowley et al., 2000)* causing scholars argue that a contingency approach towards structural embeddedness and innovation might be most appropriate *(Ahuja, 2000a; Podolny, 2001; Vanhaverbeke et al., 2008).*

Positional embeddedness. Positional embeddedness captures the impact of the position organizations occupy in the overall structure of the alliance network *(Gulati & Garguilo, 1999).* Central positions[2] in the overall alliance network increase visibility and perceived status in the overall network which provides opportunities as firms line up to partner with these central firms *(Gulati, 1999).* Another benefit of a central position is information-advantage *(Freeman, 1979)*, as central firms are positioned in-between various flows of knowledge and technologies which enables them to tap into the knowledge of a wide set of contacts and to make a good assessment of the quality of the technological portfolios of these firms. Empirical findings are very conclusive on positional embeddedness as multiple studies in various setting reported a positive relationship between centrality in the alliance network and innovative performance *(Ahuja, 2000a; Baum, Calabrese & Silverman, 2000; Hagedoorn & Schakenraad, 1994; Owen-Smith & Powell, 2004; Rothaermel & Deeds, 2004; Shan, Walker & Kogut, 1994; Stuart, 2000).*

Industrial embeddedness. Industrial embeddedness examines the effect of the whole alliance network configuration within a sector or industry on the innovative performance of the embedded firms. Firms embedded in high-tech industries engage more frequently in partnerships than firms embedded in medium-tech or low-tech industries *(Hagedoorn, 2002; Rowley et al., 2000; Schilling & Phelps, 2007)*, which influences the availability and flow of knowledge and resources within these alliance networks. Recent empirical insight indicates that embeddedness within an alliance network that exhibits high clustering and reach (*short average path length to a wide range of contacts*) stimulates innovative performance *(Schilling & Phelps, 2007).*

[2] Within the scope of this thesis we measure centrality based on horizontal technology-alliances in the industry under study. Hence, we do not include non-technology based alliances and/or alliances that are established within other parts of the value chain. Thus, central positions in the overall alliance network do not relate to companies' position in the value chain.

1.3 Clique embeddedness and innovation.

While the performance consequences of embeddedness in firm-level ego networks and industry-level inter-firm networks are increasingly well understood, there is still a shortage of studies that examine the role of intermediate network substructures -cliques- that lie in-between these distinct levels of analysis *(Rowley et al., 2004).* Studying cliques will enable us to investigate some of the unexplained variance of why some networks and positions provide greater benefit to their members than to others. Hence, from a network perspective, the effectiveness of a firm's participation in technology-based alliances could also be unevenly distributed because companies show noteworthy variations in terms of the clique(s) in which it is embedded. However, if and under what conditions clique-embeddedness affect the innovative performance of the embedded firms is largely unknown. Research on cliques has gained momentum within the literature as networks in most high-tech sectors have become larger and progressively more dense, which increases the likelihood that networks show fragmentation and clique-like structures – i.e. local clustering and shortcuts – subsequently *(e.g. Gomes-Casseres, 1996; Padula, 2008; Rosenkopf & Padula, 2008; Vanhaverbeke & Noorderhaven, 2001; Watts, 1999).* Within an alliance network, cliques are subsets of companies with relatively strong, direct, intense, frequent and/or positive ties *(Wasserman & Faust, 1994).* Cliques can be distinguished from other parts of the network by their large number of within group ties with few, if any, relation beyond *(Burt, 1992; Nohria & Garcia-Pont, 1991).* Cliques are generally viewed as one of the most powerful source of embeddedness since firms are mainly influenced by its most direct set of business partners. Prior research indicates that clique-membership positively affects performance in industries such as health care *(Provan & 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 performance and operational performance *(Rowley et al., 2004; Lazzarini, 2007),* but the effects of clique-membership on innovative performance remain unknown.

According to Lazzarini (*2007, p. 346*) "clique-membership benefits stem from the possibility to internalize positive externalities emanating from the presence of other firms in the group". This presence allows for interaction with a larger set of stable partners which enables the exchange and integration of greater and richer amounts of knowledge and technologies *(Gomes-Casseres, 1996 Lazzarini, 2007; Rowley et al., 2004).* In this sense, clique-members are able to profit from some of the same benefits attributed to relational and structural embeddedness as cliques are dense structures with many strong and redundant relationships. Cliques are however also a distinct form of embeddedness, as cliques go beyond the characteristics of the dyad and ego-network level of analysis. One of the main goals of this dissertation is to extent our current knowledge about the effect of technology-based alliances on innovative performance by investigating the opportunities and threats stemming from clique-embeddedness. As the above overview indicates that not much is known about the relationship between clique-embeddedness and innovative performance, this study will explore if and under what conditions a clique strategy is beneficial for the innovative performance of the firm.

1.4 Micro-dynamics of network evolution from a clique-perspective.

While the first goal of this study is to extent our current knowledge about the effect of dynamics in technology-based alliances on innovative performance, the second goal is to extent current knowledge on the exogenous and endogenous drivers of network change itself. Improving our knowledge and understanding about how networks and network positions emerge, take shape and dissolve is important as this can help assist companies to actually improve their position within the overall alliance network over time *(Rowley & Baum, 2008).* As described in the previous section, firms' embeddedness in technology alliance networks provides opportunities as it enables them to access knowledge and technologies externally. However, as will be described below, firms' embeddedness in technology alliance networks can also provide threats as firms' embeddedness in alliance networks can also lead to behavioral pressure.

Research on network endogeneity has demonstrated that alliance networks undergo predictable and path-dependent changes as network endogenous processes determine how alliance networks evolve and change over time *(Ahuja, 2000b; Baum, Shipilov & Rowley, 2003; Garguilo & Benassi, 2003; Powell et al., 2005; Stuart, 1998; Tsai, 2000)*. Gulati and Garguilo (*1999*) were among the first to provide empirical evidence indicating that a firm's prior position in the alliance network influences its opportunities to form new ties. Their research findings indicate that companies with prior cooperation, common third parties, and a central network location are more likely to establish new ties amongst each other *(Gulati & Garguilo, 1999).* Other papers that focused on the influence of the existing alliance network on new tie formation processes also observed that embeddedness within alliance networks leads to behavioral pressure to conform and keep relationships going, fueled by the wish not to endanger the relationship by behaving in an opportunistic way. These forces internal to the existing alliance network lead to durable and self-reproducing network positions, as firm behavior increases repeated ties among the already embedded firms *(Baum, Shipilov & Rowley, 2003; Gulati & Garguilo, 1999; Powell et al., 2005).* Over time, this so-called *structural differentiation* segments the overall network into semidetached cliques of repeatedly cooperating sets of firms. This desire to keep existing relationships going is even more the case in highly redundant and dense networks as group pressures force firms to conform their new partnering behavior to not harm group norms. Hence, network endogenous dynamics lead firms to over-emphasize their involvement with the same set of partners which could result into serious dangers for innovative performance as over-embeddedness generates decreasing opportunities for learning and innovation *(Hagedoorn & Frankort, 2008; Uzzi, 1997)*. For example, authors argue that firms that maintain strong ties amongst each other have the tendency to become more similar over time providing these firms with access to knowledge and technology with a lower novelty value *(Brass, Butterfield & Skaggs, 1998; Granovetter, 1973; Gomes-Casseres, Hagedoorn & Jaffe, 2006; Mowery, Oxley & Silverman, 1996).* Over-embeddedness has implications for clique-members as the potential for finding useful new partnerships that generate new knowledge declines within their existing group of firms *(Duysters & Lemmens, 2003; Kenis & Knoke, 2002).*

One of the main goals of this dissertation is to extent our current knowledge about the exogenous and endogenous drivers of network change by incorporating clique topology – i.e. local clustering and shortcuts. By looking at the effects of clique embeddedness on new tie formation we are able to look beyond the existing theories of network evolution since it allows to exploring if different dynamics describe alliance formation within, between and beyond these local clusters *(Rosenkopf & Padula, 2008)*. Furthermore, it allows emphasizing some of the contingencies and complementarities of cohesive networks vs. sparse networks *(Burt, 1992; Coleman, 1988).* Finally, it also allows to link micro and macro-levels of analysis in network literature *(Schilling & Phelps, 2007).* While existing theories of network evolution provide valuable insights into the rationale and mechanisms underlying new tie formation *(e.g. Ahuja, 2000a, 2000b; Gulati, 1995a, 1995b; Gulati & Garguilo, 1999; Hagedoorn, 1993, 1996; Nohria & Garcia-Pont, 1991; Silverman & Baum, 2002; Stuart, 1998, 2000)*, there is only a handful of studies investigating the dynamic differentiation of ties in terms of their network structural properties relating to the clique. One notable exception is the study of Baum, Shipilov & Rowley (*2003*) where the joint effects of events external and forces internal to the existing alliance network on the formation of new *clique spanning ties –ties linking firms in different cliques*- are explored within the environment of Canadian investment banks. Another exception is the recent study by Rosenkopf & Padula (*2008*) who empirically tested the micro-dynamics behind partner selection within the technological environment of the mobile communications industry, i.e. the formation of *clique spanning ties* and the *entry of new firms to the main component*. Surprisingly, research within this field has neglected the effects of technology as an external driver of alliance network change at the clique level of analysis. Within the domain of technology alliance networks, the effects of technology as an external driver of alliance networks change has been explored at different levels of analysis. The majority of these studies focused on the firm, the dyad, and the network level of analysis *(Ahuja, 2000b; Katila & Mang, 2003; Madhavan, Koka & Prescott, 1998; Stuart, 1998).* While most research findings on structural differentiation indicate that the evolution of network structures lead to a definite structural pattern over time, it is very likely that these effects are not the same in every industry setting. According to Gulati & Garguilo (*1999; p.1478*) "*a different force* might be in place in new, extremely dynamic and innovation driven industries, where all players could benefit from alliances with almost any other player". In these industries, competition puts increasing demands on firms to keep their technological knowledge bases competitive, forcing firms to overcome their tendency to be locally biased and path dependent in their search processes to form new ties *(Gulati, 1995a; Stuart & Podolny, 2000; Walker, Kogut & Shan, 1997).* As the above overview indicates that not much is known about how technological portfolios affect network evolution from the perspective of the clique, this study will explore how technological portfolios counterbalance the process of structural differentiation.

1.5 Research Question.

As motivated within the previous sections, embeddedness within alliance networks of interconnected companies provides opportunities as well as constraints. A firm's network provides valuable inputs but firms are also relationally bounded to its current set of partners as path dependency and local biases influence a firms' new alliance formation pattern. This dissertation will address the literature on alliance network dynamics and innovation by focusing on the reciprocal relationship between alliance network dynamics and innovation from a clique-perspective. Therefore, the research question of this dissertation is as follows:

> *How do network positions and technological portfolios influence the innovative performance of clique-members and how can clique-members reposition themselves beyond the scope of their clique?*

This research has been partitioned into two sub-sections, which makes it more systematic to answer the main research question. Both sections are interrelated given that both shed light on one particular aspect of the research question. The first section extends our current knowledge about the effect of dynamics in technology-based alliances on innovative performance by investigating the opportunities and threats stemming from clique-embeddedness. The second section extends our current knowledge about the exogenous and endogenous drivers of network change by incorporating clique topology – i.e. local clustering and shortcuts – into the existing theories of network evolution. Below these sections are discussed into more detail and are marked out how these sections relate to the main research question.

Section 1: Clique embeddedness and innovation.
This section will focus on the relationship between clique-membership and *innovative* performance. It extends our current knowledge about the effect of dynamics in technology-based alliances on innovative performance by exploring the opportunities and threats stemming from clique-embeddedness. Clique-members have strong and repeated interactions with stable partners which enables them to pool and transfer technological knowledge and capabilities more deeply and at a higher pace. While these aspects of clique-embeddedness give reasons to expect a positive relationship between clique-embeddedness and innovative performance, there are also reasons to expect that these positive benefits are not distributed equally over all clique members. Within this section two conditions will be addressed which might explain variations between clique members in terms of their potential to improve their innovative performance based on the embeddedness within the clique: (*1*) its position within the clique and (*2*) the (in) ability of clique-members to adapt to technological changes.

First, embeddedness within the clique is generally expected to be beneficial for a firms' innovative performance as the presence of other firms within the clique allows for the exchange and integration of greater and richer amounts of knowledge and technologies *(Gomes-Casseres, 1996 Lazzarini, 2007; Rowley et al., 2004).* However, there are also reasons to expect that clique-embeddedness is not equally beneficial to all firms within the clique since a firms' position inside the clique determines the extent to which it can tap into heterogeneous sources of knowledge and technology. Network endogenous dynamics lead firms inside these highly redundant and dense ego-networks to over-emphasize their involvement with the same set of partners, as group pressure forces firms to conform their new partnering behavior to not harm group norms. This could become a serious threat to the innovative performance of some clique-members as they become over-embedded inside their clique and face decreasing opportunities for learning and innovation inside their clique *(Hagedoorn & Frankort, 2008; Uzzi, 1997).* These potential dangers will especially be manifest in companies' explorative capabilities since their network does not enable them to explore novel domains *(Rosenkopf & Almeida, 2003).*

A second reason to expect that clique-embeddedness is not equally beneficial to all firms within the clique stems from the (in)ability to adapt to technological changes. Technological changes form a serious threat to clique-members as new technologies originate in many cases from peripheral companies that challenge market leaders *(Christensen, 1997; Christensen & Raynor, 2003).* Turbulent environments require a network position that facilitates exploration of new knowledge, while stable environments emphasize the importance of network positions that enable exploitation of current knowledge *(Burt, 2000; Rowley et al., 2000).* Hence, clique-membership could also become a serious threat to the innovative performance of the embedded firms during technological change as firms need to explore new knowledge and technologies while the existing knowledge pool inside the clique is not able to facilitate this. Consequently, technology shifts give clique-members a clear incentive to strategically redesign their networks and reconsider their position as clique-member. In order to gain a deeper insight into the effect of technological uncertainty on the effectiveness of clique-embeddedness this study investigates some of the underlying mechanisms of clique-embeddedness which become relevant during these periods of uncertainty: the opportunity to access novel sources of knowledge and technology within the clique and the (in)ability to adapt during these periods.

Section 2: Micro dynamics of network evolution from a clique-perspective.
This section extends our current knowledge about the exogenous and endogenous drivers of network change by incorporating clique topology – i.e. local clustering and shortcuts – into the existing theories of network evolution. More in depth, it will explore which factors enable clique-members to reposition themselves beyond the scope of the clique. While most studies have shown motives why firms tend to be locally biased and path-dependent in their search strategies *(Gulati, 1995a; Stuart & Podolny, 2000; Walker, Kogut & Shan, 1997)*, relatively less is known about situations in which firms may opt for forming a clique spanning tie. Despite the dangers of over-embeddedness firms have a preference to establish new alliances with members of their current clique *(Baum, Shipilov & Rowley, 2003).*

To date, Baum, Shipilov & Rowley (*2003*), and Rosenkopf & Padula (*2008*) have provided a baseline model to jointly explore the effects of exogenous and endogenous drivers of network change on the formation of clique spanning ties. Their research findings indicate that a firms' position in the existing alliance network determines its opportunities to establish ties outside the boundaries of the clique. However, to our knowledge no prior research focused on the role of firms' technological knowledge bases as a driver of the establishment of clique spanning ties. Especially within extremely dynamic and innovation driven industries this might be a strong facilitator of micro-dynamics inside the alliance network. Prior research indicates that a firm's attractiveness to potential partners and hence its opportunities to collaborate are likely to vary positively with its technological knowledge base *(Ahuja, 2000a; Dutta & Weiss, 1997; Katila & Mang, 2003; Rosenkopf & Almeida, 2003; Stuart, 1998; Zhang, Baden-Fuller & Mangematin, 2007).* While these findings indicate that a positive relationship exists between a firms' knowledge base and the number of linkages formed by the firm, we do not know if a firms' knowledge base also affects clique-members' ability to reposition themselves beyond the scope of their clique. Therefore, this section will explore how firms' technological knowledge base and its position in the existing alliance network influence its potential to go beyond local search in the alliance network.

1.6 Structure of the dissertation.

This dissertation is organized as follows. Chapter 2 describes the industry setting and the research design. The main purpose of this chapter is to define the industry setting and explain why it makes an interesting and appropriate setting for this dissertation. This chapter also presents all relevant background information and descriptive statistics related to the data-sources that have been used to construct the data-set. The following three chapters will focus on one the research sections that were described earlier. The first two empirical chapters (*chapter 3 & 4*) use network dynamics and repositioning as an independent variable and aim to expand our knowledge about the relationship between clique membership and innovative performance. Chapter 3 is the first empirical chapter and looks at the effect of firms' position within the clique on its innovative performance. Chapter 4 addresses another mechanism which might endanger the innovative performance of clique-members: the (in)ability of clique-members to adapt to technological changes. Chapter 5 is the last empirical chapter and looks at how a firm's network position and technological knowledge base affect its potential to establish ties beyond the scope of their clique. Hence, network dynamics and repositioning are the variables of interest in this chapter. Chapter 6 provides a summary and discussion of the main results, the limitations of the current study, the directions for future research and the contribution of this dissertation to both social network theory and practice.

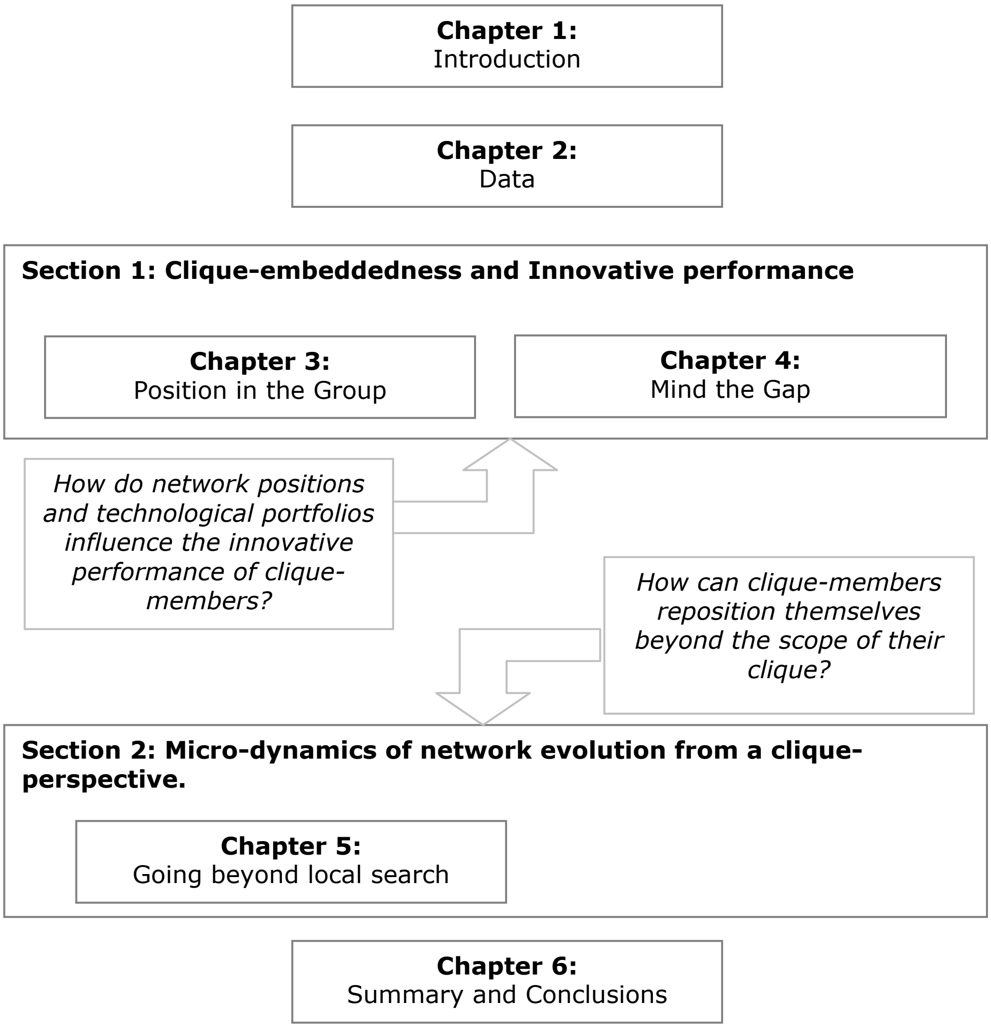

Figure 1: Overview of dissertation.

Chapter 2: Data and Sample

Chapter 2: Data and Sample

2.1 Introduction.

To be able to answer the research questions formulated in the previous chapter, a longitudinal database was set up. The objective of this chapter is to provide an overview of how this longitudinal database was constructed. For the purpose of this dissertation, data was collected on cooperative, technological and financial activities of companies operating in the international industry of Application Specific Integrated Circuits *(from now on: ASIC-Industry).* The ASIC-industry is a sub-sector of the semiconductor industry. Semiconductors process, store and move pieces of information that is critical for the operation of electronic devices such as calculators, computers, cell-phones, televisions and even most contemporary automobiles. Semiconductors are literally an unseen part of our everyday life and are generally considered as "the crude oil of the information age" because of the tremendous influence of semiconductors on our economy. Semiconductor-sales passed $200 billion in the year 2000, making it one of largest industries worldwide. This chapter is organized as follows. First, a more detailed background of the industry and motivation for choosing this industry are discussed. Second, a comprehensive description of the data-sources that were utilized to construct the longitudinal database is provided. Third, descriptive statistics are presented regarding the most important aspects of the longitudinal database: indicators of cooperative, technological and financial activity of ASIC-companies.

History of the Semiconductor industry. The invention of the transistor at the laboratories of AT&T (*Bell labs*) in 1947 marks the beginning of the semiconductor industry. A transistor is a device that can be used to amplify or switch electronic signals. Another technological breakthrough occurred in 1958 and 1959 when engineers Jack Kilby (*Texas Instruments*) and Robert Noyce (*Fairchild*) developed the first integrated circuit. The introduction of the integrated circuit allowed having more than one transistor on a single chip and the interaction of these transistors with each other. The integrated circuit led to massive cost savings and enormous performance benefits as the production process could be optimized to include as much transistors as possible[3]. The introduction of the integrated circuit marked the beginning of a complex evolutionary miniaturization trajectory characterized by various incremental and radical innovations. This miniaturization process in which the number of transistors per chip doubled every two years has been named Moore's law *(Moore, 1965).* The history and development of the semiconductor industry has often been used in literature by various authors describing the underlying evolution and dynamics of the industry *(Dosi, 1984; Malerba, 1985; Langlois &*

[3] Appendix 1 describes the process of semiconductor manufacturing at more length

Steinmueller, 1999). Industrial developments and information about companies are very well documented making it a suitable industry to utilize in empirical research.

From the beginning, the semiconductor industry has been very competitive. Initially, the market was dominated by large U.S. electronic companies but due to its low entry barriers a wave of new specialized entrepreneurial firms entered the industry *(Hannan & Freeman, 1989).* Soon after their entry these specialized entrepreneurial firms started to outperform the large electronic companies as these companies were unable to adapt their core competences and business models to compete on this highly demanding market *(Christensen & Rosenbloom, 1995; Langlois & Steinmueller, 1999; Duysters, 1996).* Later the industry became a global industry as large integrated firms in Europe and Asia were attracted by the high returns on investments. Sometimes, these companies were backed-up by their governments as they recognized the importance of the industry for the national economy and the spill-over effects of semiconductors to other industries. The presence of large amounts of capital to invest and the extreme complexity of the mass-production process resulted in an ever-present fierce competition within the industry. The industry has been technological driven throughout its history requiring extremely high R&D costs (*exceeding 10% for most companies*) to develop new technologies *(Podolny & Stuart, 1995).* Furthermore, the production of semiconductors is very challenging and requires huge capital investments and large volumes of production to amortize the costs *(Jelinek & Schoonhoven, 1990).* The overall demand of semiconductors has a very cyclical nature making the strategic planning and investment decisions cumbersome. The complexity of developing new generations of products forced companies all over the world to form strategic alliances beyond their nationalistic boundaries *(Duysters & Hagedoorn, 1998; Gomes-Casseres, 1996; Stuart & Podolny, 2000).* In sum, developments within the semiconductor industry have been extremely dynamic and innovation driven since the beginning, with various observable changes in technological regimes accompanied by the entry and exit of various different companies. The industry is diversified in terms of organizational forms, company strategies, underlying technologies and products offered to the market.

Characteristics of the ASIC-industry. The ASIC-industry is a subset of the semiconductor industry and has its own products and underlying technologies. In contrast with general purpose semiconductors such as microprocessors or memory chips, ASICs are specifically designed for one customer to perform only one particular function. The decision to custom design semiconductors or to use standard semiconductor devices is a major consideration for many electronic companies as a good custom-designed semiconductor leads to significant competitive advantages. End-users usually make a trade-off between the relative costs and benefits of ASICs compared with off-the-shelf standard semiconductors *(see table 1).* ASICs become a viable option at around 250.000 units of production since these volumes are able to decrease the marginal costs of developing and designing ASICs efficiently *(Turley, 2003).*

Table 1: Trade-off between Standard ICs and ASICs.

Standard ICs	ASICs
Lower cost due to mass production	Expensive due to higher design costs
Off-the-shelf availability	Longer lead-times (not including PLDs/FPGAs)
Proven reliability (fully tested)	Potential for failures (custom designs)
Multiple manufacturers and vendors	Single sourcing, potential for delivery delays
Not optimized for each system	More usable gates, higher speed, space efficiency
Difficult to obtain differentiation	Potential for competitive advantage

ASIC-technology itself has been around since the early 1970s, but the industry did not get into serious development until the early 1980s when various electronic devices such as house-appliances and the desk-top computer became a hit. Due to the success of these products, electric companies were more and more willing to pay for the design of a custom made integrated circuit, besides the fixed costs of manufacturing. The ASIC-market was initially dominated by large U.S. semiconductor producers[4] who were gradually pushed out of other parts of the highly competitive semiconductor market where the main source of competition gradually shifted towards low prices and high production volumes. These companies saw the ASIC-market as a lucrative niche where value could be added based on their technological expertise and service. However, just as within the global semiconductor industry, increasing complexity and specialization of ASIC-products and technologies started a process of start-ups and spin-offs. Between 1980 and 1990 companies fully focusing on ASIC design and/or manufacturing entered the market[5] *(Einspruch & Hilbert, 1991).* Over the years, firms competing in the ASIC-industry emerged throughout the world, with the majority of firms located in the US, Japan and Europe. The ASIC industry has been a driving force behind major technological breakthroughs in the semiconductor industry. Just as within the semiconductor industry, the complexity of developing new generations of products forced companies all over the world to establish horizontal strategic alliances aiming to improve their technological knowledge base *(Vanhaverbeke, Duysters & Noorderhaven, 2002; Beerkens, 2004).* Overall, these characteristics make the ASIC-Industry an attractive industry to study how alliance networks emerge and evolve over time and how these network dynamics influence the innovative performance of the embedded firms.

[4] With large electronic companies that produced ASICs for internal needs (*e.g. IBM or Texas Instrum.*).
[5] See appendix 2 for an overview of all relevant players and their interactions within the ASIC-Industry.

The ASIC market itself can roughly be divided into three sub-segments namely: gate arrays, standard cells/full custom designs and programmable logic devices[6]. ASIC-vendors can be exclusively involved in the production of one of these three segments, or in more segments at the same time. Segments are important in the sense that firms in each segment face different technologies, competitors and competitive or technological dynamics, up to a certain point because all realize the same system functionalities. Customers typically make a decision between these three ASIC-segments based on the total cost per chip, which is dependent on the production volume and their design complexity. Programmable logic devices are the cheapest solution for simple and low volume production and standard cells/full custom designs are the most efficient solution for production volumes that exceed several hundred thousands of ASICs.

2.2 Data sources.

Overview. For the construction of the longitudinal database on cooperative, technological and financial activities of ASIC-companies various secondary data-sources was collected. The use of secondary data allows for rapid access to large amounts of data which can be processed at a high pace. Working with secondary data has also some limitations as not all these data sources were originally collected with the goal to capture the underlying strategic processes and intentions of the focal firms. In order to collect the most appropriate information regarding cooperative, technological and financial developments within the ASIC-Industry various publicly as well as not-publicly accessible data were colected *(See table 2).* To be able to access the most relevant non-publicly accessible data, cooperation was setup with two research institutes namely Chipworks located in Ottawa, Canada and UNU-MERIT located in Maastricht, the Netherlands. The data sources that are used within the scope of this dissertation are described below.

Table 2: Overview of data sources.

	ICE-Report	CATI	Derwent	USPTO	Compustat
1. Sampling of firms	x				
2. Cooperative indicators	x	x			
3. Technological indicators			x	x	
4. Financial indicators	x				x

ICE Industry Reports. Before being acquired in 2000 by Chipworks, the ICE-Corporation was a leading market research company delivering global market analysis reports of the semiconductor market. With generosity of Chipworks the following industry reports were used within this dissertation: the ASIC-Outlook

[6] See appendix 3 for an overview of all formal definitions.

Reports (*1987-2000*); the ICE-Company Profiles (*1991-2000*) and the ICE-Status Reports (*1980-2000*). The ASIC-Outlook Report (*1987-2000*) is an annually published professional journal with detailed background information on developments and forecasts within the ASIC-Industry. The ASIC Outlook Reports have been the main source of information for business analysts within the ASIC-Industry. As the directory covers all significant developments regarding the industry as a whole and the most important ASIC-companies, it provides a valid reflection of the underlying evolution and dynamics within this industry. The ICE Company Profiles (*1991-2000*) is a world-wide survey of semiconductor manufacturers and suppliers. The yearly single volume publication profiles over 175 semiconductor companies. Each company's profile covers: sales history, overviews & strategies, key management personnel, products & process capabilities, IC facility information, and key present and proposed strategic agreements. The ICE-Status Reports (*1980-2000*) are annual publications which include comprehensive updates and forecasts of the global semiconductor industry. Furthermore, these reports provide detailed information regarding the technological, cooperative and financial developments of the most significant companies that service this industry.

MERIT CATI. The MERIT-CATI database *(Hagedoorn, 1993)* is a relational database with data on approximately 12.000 technology-related inter-firm partnerships within the time period 1960 - 2008. With generosity of UNU-Merit this unique database, which contains information on cooperative agreements in various industries and on the companies participating in these agreements, has been used within this dissertation. For the construction of this database the makers relied on various data-sources such as newspapers, journal articles, books, and specialized journals reporting on business events. A large body of prior empirical research on technology partnerships is based on the MERIT-CATI database *(e.g. Hagedoorn, 1993; Hagedoorn & Schakenraad, 1994; Duysters & Hagedoorn, 1996; Gulati, 1995a; Gulati & Singh, 1998)*.

Derwent World Patent Index. The Derwent World Patent Index ® (*DWPI*) is the world's most comprehensive database of enhanced patent documents. Derwents' experts analyze, abstract and manually index every patent record, which offers a complete picture of all relevant technological developments within an industry. DWPI contains over 15 million records covering more than 35 million patent documents, with coverage of over 41 major patent issue authorities worldwide.

USPTO. The United States Patent and Trademark Office (*USPTO*) patent database includes full-text information for all patents applied in the United States. Patent information provided by the USPTO includes inventor and company information, application data, year the patent was granted, citations to prior patents, and detailed technological information. According to the website of the USPTO, "the right conferred by the patent grant is the right to exclude others from making, using, offering for sale, or selling the invention in the United States or "importing" the invention into the United States." While the use of the USPTO database could potentially lead to a bias towards U.S. companies, past research indicates that, given the importance of the U.S. market, most companies worldwide file patents within the U.S. *(Patel & Pavitt, 1991).*

Compustat. This database contains financial information on approximately 15.000 active and inactive firms in 70 countries. The data is collected using consistent sets of financial data items that are developed by examining financial statements from a variety of countries and identifying items that are widely reported by companies regardless of their geographic location, business activity or accounting practices. Data is carefully validated and consistently reported, which allows for a highly detailed presentation of company fundamental data that takes into account the various international accounting standards seen in the world today.

2.3 Description of the data.

Sampling of firms. This thesis is based on a longitudinal research design within a single-industry. Research a single-industry allows for a profound examination of the influence of firm and network characteristics on outcomes such as performance and new tie formation *(Stam 2008; Van de Vrande, 2007).* Although the use of a multi-industry study would lead to greater generalizability of the empirical data, studying a single sector has the advantage of identifying and describing all relevant processes in depth. Limiting the study to a single industrial sector minimizes problems related to other factors affecting the variables of interest as these factors are likely to be stable within one context *(Cohen & Levinthal, 1989; Ahuja & Katila, 2001).*

In order to build up a database that following the main trends and developments within the ASIC-industry, all relevant firms that offered these ASIC-products to the merchant between 1987 and 2000 market were selected. A detailed list of these companies was established based on the ASIC-Outlook Reports. Within these reports a vendor directory was included which covered detailed background information on all relevant ASIC-Vendors. The directory was compiled from firms' promotional material, industrial trade publications, and personal telephone industries. In order not to miss important developments within the industry, all captive firms that produced ASICs were manually included. Including these companies in the database allows correcting for the fact that some large companies produce ASICs only for their internal needs. These companies represent a small minority of ASIC-producing companies but are nonetheless important in terms of technological capabilities (*e.g. IBM and*

Texas Instruments). In total 158 companies were included as relevant ASIC vendors within the time period 1987-2000. A list of these companies, along with background information and descriptive statistics is presented in appendix 4.

Cooperative activities. The data used in this dissertation relate to strategic alliances of which the major focus is on technological developments in the ASIC-industry. Following Hagedoorn (*1993*), a cooperative arrangement was defined as "a common interest between independent (industrial) partners which are not connected through (*majority*) ownership". Within a high-tech environment, firms are likely to establish strategic alliances among each other in order to keep up with the newest technologies (*Duysters & Hagedoorn, 1996*). As in other branches of the IC industry, technological knowledge acquisitions are by far the most important reason why firms team up with each other in the ASIC-Industry (*Vanhaverbeke, Duysters & Noorderhaven, 2002*).

Data on strategic alliances were collected for the period 1982 – 2000, a period that was characterized by strong industry turbulence due to the establishment of numerous strategic alliances *(See Figure 2).* A detailed list of all relevant publicly known ASIC-related cooperative agreements was based on the MERIT-CATI database *(Hagedoorn, 1993)*, the ASIC-Outlook Reports (*1987-2000*) and the ICE-Company profiles (*1991-2000*). Included were all alliances that focused on transferring technology or joint research. Following Stuart (*1998*) all one way technological license agreements and second source agreements were excluded as these alliances are often formed for reasons that do not have to do with the exchange or development of technology, e.g. a standard setting strategy by licensing or coping with uncertainties in production cycles by establishing a second source agreement. A distribution of the alliances by type is presented in appendix 5.

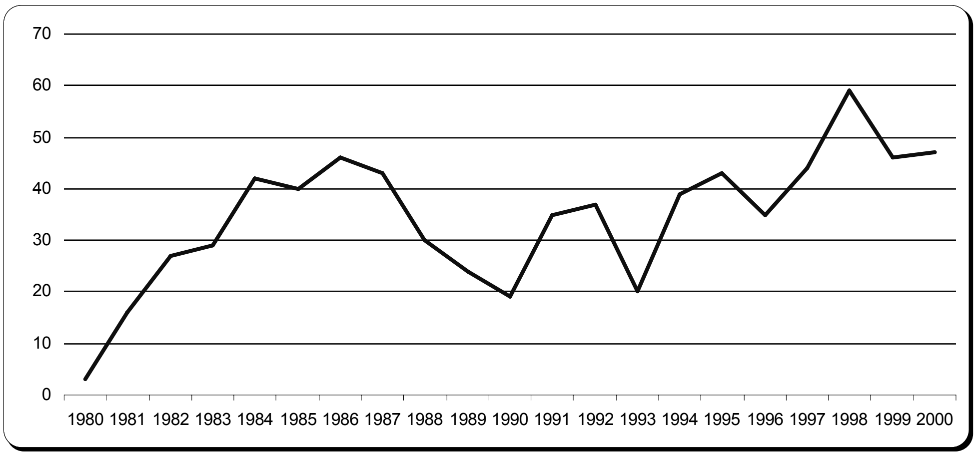

Figure 2: Cooperative activities in the ASIC-Industry (1980-2000).

For the construction of the alliance networks a 5-year moving window approach *(Kogut, 1989, Gulati 1995a)* was used to construct the alliance networks. This is in line with prior literature that suggests that only ongoing alliances have an impact on the variables of interest. These networks were lagged one year in order to regress these independent variables with the appropriate dependent variables. Hence, the 14 alliance networks (*e.g. 1982-1986; 1983-1988; 1984-1989 etc*.) derived valuable statistics on the alliance network positions of the ASIC-companies.

Technological activities. The ASIC-industry is a typical high-tech industry where technology is the driving force shaping competition among firms and where R&D-to-sales ratios are exceptionally high. The growth of ASIC technology has been fueled by competitive pressure and continuing requirements for higher levels of integration in electronic systems to meet performance, cost, and quality goals.

A detailed list of all technological activities was based on the DWPI® and the USPTO patent database. 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, 2000a; Stuart, 2000; Hagedoorn & Duysters, 2002; Schilling & Phelps, 2007).* The use of patents has been criticized on many occasions and on many grounds *(see Grilliches, 1990 for an overview).* Despite these shortcomings, patents are generally regarded as the most appropriate measure of innovative performance at the company level, especially within a single sector context *(Acs & Audretch, 1989; Hagedoorn & Duysters, 2002).* In particular in industries where companies operate on a global scale, such as the ASIC-industry, U.S. patents are a good proxy for companies' worldwide technological performance and technological assets (*Jaffe & Trajtenberg, 2002*).

The DWPI® numbers U13-C04C, U13-C04D & U21-C01E represent all ASIC related patents. However, the DWPI® is only available for the period 1987-2000. For our independent variables that used patents before that period 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).* Detailed data on technological activities have been collected for the period 1982 – 2000, a period that was characterized by numerous new innovations and patent applications *(See Figure 3).*

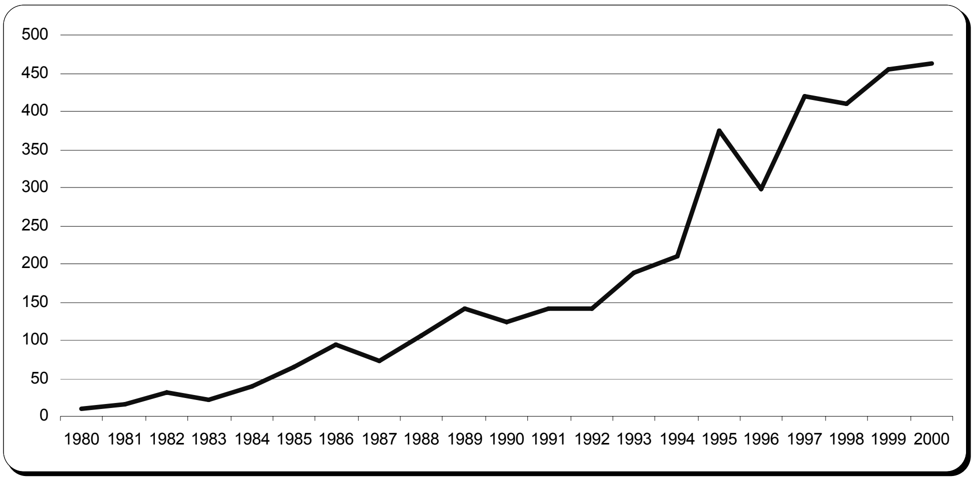

Figure 3: Technological activities in the ASIC-Industry (1980-2000).

Financial activities. Just as the broad semiconductor market, the ASIC market is a very volatile market as well. The market has experienced some exceptional growth rates, but also suffered from the intense downturns that occurred in 1998 and 2001. Because the innovative performance of companies is not only depending on firms' cooperative activities, data on firm-specific characteristics was also obtained. Financial data were collected for the period 1987-2000, a period that captures a major part of the growth in overall sales within this industry *(See Figure 4).* Data on firms' revenue stream and R&D expenditures controls for firm-level variations in innovative performance. These data are based on the ASIC-Outlook Reports (*1987-2000*); the ICE-Company profiles (*1991-2000*) and Compustat. Unfortunately the data did not allow for determining full financial portfolios of all included companies, with most of the missing observations arising from the lack of disclosure of smaller and/or private companies.

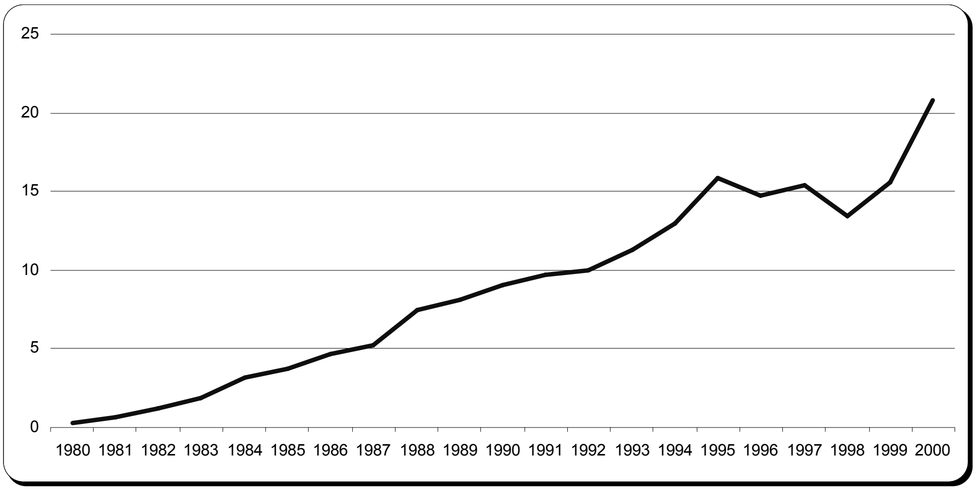

Figure 4: Total ASIC sales per year ($B) (1980-2000).

2.4 Balancing theory and technique: Alliance cliques.

Research on subgroups within industries has had a large appeal on strategy researchers and industrial economists (*Porter, 1979*), in view of the fact that these intra-industry groups have the potential to link macro-structures of an industry with the micro-level strategic behavior of individual firms (*Granovetter, 2005*). While research on strategic groups flourished during the 1980s, it faced substantial criticism (*Barney & Hoskisson, 1990*) due to an "existence" problem as researchers could not provide irrefutable evidence that strategic groups were more than merely a categorization of some basic firm characteristics[7]. In order to have a more meaningful ontological status, groups need to have a behavioral basis, some sort of mutual awareness and need to contribute to firm performance (*Shanley & Peteraf, 2005*). Research within the field of strategic networks and alliances has the potential to provide meso-level research with the required theoretical and methodological basis because groups, in network terms, are sets of firms with relatively dense interaction patterns relative to non-members (*Shanley & Peteraf, 2005*). Hence, the relational profiles within an industry offer the behavioral basis and mutual awareness needed for a meaningful ontological status of subgroups.

In recent years, cliques gained significance in literature on inter-firm relations as networks in most sectors have become larger and increasingly dense, increasing the likelihood of network fragmentation subsequently (*Baum, Shipilov & Rowley., 2003; Lazzarini, 2007; Rowley et al., 2004, 2005)*. Within network literature, cliques

[7] Empirically, clustering techniques were used to detect relevant strategic groups based upon the categorization of firm characteristics.

are subsets of actors among whom there are relatively strong, direct, intense, frequent and/or positive ties *(Wasserman & Faust, 1994).* Hence, substructures can be distinguished from other parts of the network by their large number of within group ties will they tend to have few, if any relation beyond *(Burt, 1992; Nohria & Garcia-Pont, 1991).* Operationally, the boundaries of cliques in inter-firm alliance networks can be distinguished by explicit or implicit assumptions *(Lazzarini, 2007).* Explicit cliques are bounded together by very formal and collective arrangements, such as a multilateral agreement which includes collective governance mechanisms and/or a joint strategy. The importance of research on explicit cliques has been widely recognized and is well accepted within the strategic and managerial literature. Explicit cliques are observable within and across all stages of the value chain and within various industries. Examples of explicit cliques are alliance constellations such as observable within the global airline industry *(e.g. Star Alliance: Lazzarini, 2007),* R&D consortia such as observable within the semiconductor industry *(e.g. Sematech, Browning, Beyer & Shetler, 1995)* or standard setting cliques such as observable within the computer industry *(e.g. Unix, Axelrod et al., 1994).*

Implicit cliques involve companies that are more densely interconnected to one another than to other companies within the alliance network *(Baum, Shipilov & Rowley, 2003; Rowley et al., 2004, 2005, Rosenkopf & Padula, 2008).* Compared to research on explicit cliques, research on implicit cliques is underdeveloped because implicit cliques lack a multilateral agreement that characterizes explicit cliques. However, the existence of implicit cliques within alliance networks has been reported by various studies (*Baum, Shipilov & Rowley, 2003; Lazzarini, 2007; Rowley et al., 2004, 2005),* it has been argued that implicit cliques have a behavioral basis (*Baum & Ingram, 2002*), and empirical evidence indicates that implicit cliques contribute to firm performance (*Lazzarini, 2007; Padula, 2008; Provan & Sebastian, 1998; Rowley et al., 2004).* For the empirical construction of implicit cliques a measure is needed that includes companies that are close in geodesic space and have a certain amount of density within the cliques since this is a signal of mutual awareness and interaction. Various techniques can be used to partition the overall alliance network into cliques. Earlier techniques have been taken from multivariate statistics (*e.g. MDS, clustering*), as well as from graph theory (*e.g. Alba, 1973; Borgatti, Everett & Shirey, 1990; Mokken, 1979; Luce & Perry, 1949; Luccio & Sami, 1969*). Recently, new developments from the field of physics signaled new methodological pathways to detect subgroups within networks (*e.g. Newman, 2004; Palla, Barabasi & Vicsek, 2007*). Statistically, cliques can be distinguished by either a top-down or a bottom-up technique, where top-down approaches partition networks into non-overlapping sets of firms. Top-down approaches cluster companies together based on an optimization of either: density, based on a pre-specified number of cliques (*factions/tabu search*); connectivity, based on a pre-specified cut-off cluster value (*Lambda sets*) or structural roles, based on a pre-specified number of splits (*Concor*). Bottom-up approaches cluster companies together based on either the minimum group-size, the maximum geodesic distance amongst clique members, the frequencies of ties amongst clique-members or a combination thereof. Hence, a wide range of methodological techniques exist to detect relevant cliques within the alliance network and theoretical considerations should drive the process of distinguishing true from spurious cliques.

Within the field of alliance networks there is no dominant method since various studies used various techniques to detect relevant cliques: Concor (*Baum, Shipilov & Rowley, 2003; Rowley et al., 2005; Rosenkopf & Padula, 2008; Vanhaverbeke & Noorderhaven, 2002*); Tabu search (*Lazzarini, 2007*) and N-Clan (*Rowley et al., 2005*). Within our specific industry we had no prior knowledge about the number of cliques within the industry and found indications that firms were not exclusively involved in only one clique. These findings made it inappropriate to use a top-down technique. Other considerations were grounded in the theoretical arguments that cliques require some sort of mutual awareness and should contribute to firm performance. Together, these arguments made the N-Clan procedure (*Mokken, 1979*) the most appropriate procedure to study cliques within the ASIC-industry. We defined the maximum geodesic distance amongst clique members at 2 steps and defined the minimum group-size at 5 participating firms. Increasing the maximum geodesic distance to more than 2 would result in an unjustifiable high amount of cliques. The minimum group-size was set at 5 participating firms in order to because of the theoretical arguments that cliques need to have a behavioral basis, some sort of mutual awareness and need to contribute to firm performance.

The next research goal was to label each new alliance based on their structural properties in relation to the clique. Figure 5 illustrates different forms of alliances that firms can establish in and outside their clique: "inside ties", "outside ties" and "clique spanning ties. For non-clique members there is also the possibility of a so-called "peripheral tie". Furthermore, the three firms in the middle of the graph are members of more than one clique *(clique 1 and clique 2).* Although these different forms of alliances are all important in its own right, the current paper focuses on clique spanning ties. These ties can lead to strategic advantages for firms who intend to maneuver themselves in a position as broker between two cliques *(Baum, Shipilov & Rowley, 2003, Rosenkopf & Padula, 2008).*

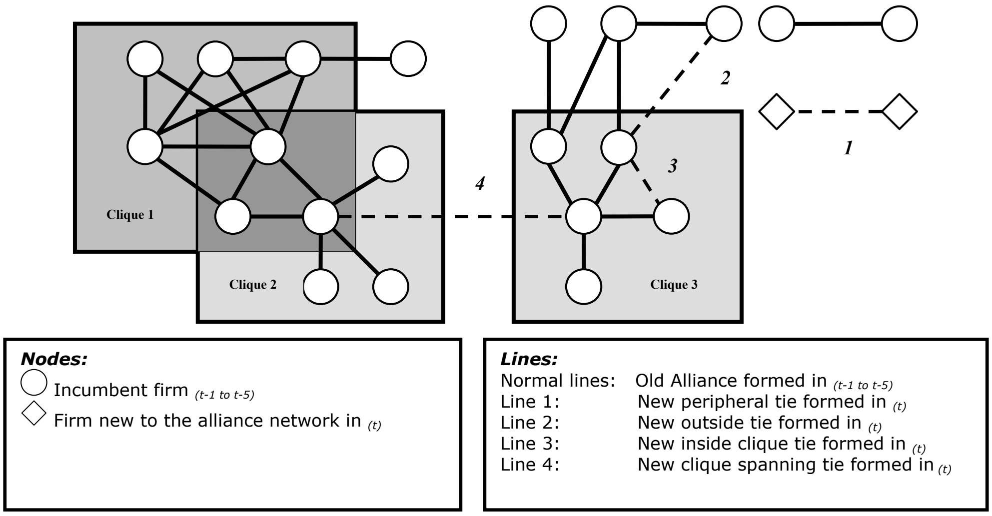

Figure 5: Alliance network with various options for new alliance formation.

Appendix 6 presents descriptive statistics about the alliance network within the ASIC-industry. The ASIC-industry shows small world characteristics, which is in line with research findings on other high-tech industries (*Verspagen & Duysters, 2004; Rosenkopf & Padula, 2008; Schilling & Phelps, 2007*). This is an indication that the overall network structure in this industry is segmented into semidetached cliques of repeatedly cooperating sets of firms with some ties that cross the boundaries of these cliques. Recent empirical insight indicates that embeddedness within an alliance network that exhibits small world characteristics, i.e. high clustering and reach (short average path length to a wide range of contacts) stimulates innovative performance *(Schilling & Phelps, 2007).* However, since small worldliness is a network level measure it can only be applied to between industry analyses. Therefore, other measures need to account for firm and clique-characteristics which are the main levels of analysis within this dissertation. Based on the N-Clan procedure, 75 firms were identified as clique-members within the period 1987 - 2000. In total we found an average of 33 cliques per year *(s.d.= 5,16; range 26-42)* during our observation period (*1987-2000*). Within this particular industry, 38% of the firms were member of more than one clique. Following Rowley et al. (*2005*) firms assigned to multiple cliques were considered to be members of each clique for purpose of computing the clique-level independent variables. We corrected the firm level observations for overrepresentation by weighting these observations by the number of cliques these firms participated in *(Rowley et al., 2005)*.

Chapter 3: Position in Groups

The impact of network position within the clique on innovative performance

Abstract

Alliance cliques have been largely neglected in technological alliance studies. In this study we show that cliques offer an interesting angle to analyze differences between firms' innovative performance. We test five hypotheses regarding the relation between clique-membership and the innovative performance of the embedded firms. Our results indicate that clique-membership does enhance a firm's innovative performance, but that not all that glitters is gold for all members of the clique. Significant variations arise from a firms position inside the clique and from its past alliance behavior.

Keywords: alliance networks; clique membership; new technologies; technology life cycle; technology profiles; innovative performance

This chapter is based on:

Pieters, M., Hagedoorn, J., Vanhaverbeke, W. & Van de Vrande, V. The impact of network position within the clique on innovative performance. *Manuscript submitted for publication*.

3.1 Introduction.

Research within the field of technology and strategic management has stressed the importance of social capital for a firm's innovative performance. Firms that are well embedded within the overall inter-organizational network gain positive externalities such as informational advantages, which can be utilized to enhance a firm's technological knowledge base. While the importance of inter-firm network embeddedness starts to become well known from the perspective of ego-network structure *(Ahuja, 2000a; Baum, Calabrese & Silverman, 2000; Capaldo, 2007; Shan, Walker & Kogut, 1994; Powell et al., 2005; Vanhaverbeke et al., 2008)* and industrial-network structure *(Rowley, Behrens, Krackhardt, 2000; Shilling & Phelps, 2007),* we know relatively less about the influence of clique-level embeddedness on a firms innovative performance.

The observation that small world characteristics are observable within inter-firm networks *(Watts, 1999)* has drawn new attention on the underlying micro-dynamics of cliques and the relationship between clique-membership and firm performance *(Baum, Shipilov & Rowley, 2003; Lazzarini, 2007; Padula, 2008; Rowley et al., 2004, 2005; Rosenkopf & Padula, 2008; Vanhaverbeke & Noorderhaven, 2001).* While these studies all contain rich theoretical and empirical insights on the causes and consequences of clique-embeddedness, they do not describe the full relationship between clique-embeddedness and innovative performance. First, prior clique-studies found a positive effect of clique-membership on financial performance and operational performance *(Rowley et al., 2004; Lazzarini, 2007),* but to our knowledge no prior research focused on the effects of clique-membership on innovative performance. Second, prior clique-research studied the effect of network position in the overall alliance network on performance *(Rowley et al., 2004),* but the effect of network position in the clique on performance remains largely unknown. One notable exception is the study by Padula (*2008*) who empirically indicated the positive effects of network position in the clique -i.e. having a balanced set of relations within and across the clique- on the innovative performance of these firms. The current study intends to fill these uncharted areas by focusing on the relationship between clique-membership and *innovative* performance and to deepen our knowledge about the effect of *position within the clique* on a firm's performance. We expect that the positive benefits of clique membership on performance are not distributed equally over all clique members and that various sources of heterogeneity stemming from position in the clique can be distinguished between clique-members relative towards each other. Therefore, in this paper we examine how a firm's position within the clique affects its ability to innovative. The results in the empirical section confirm that clique-membership plays an important role in explaining the innovative performance of firms and indicates that this relationship is indeed affected by the position of the firm within the clique.

This paper is organized as follows. First we provide a more detailed background on the hypotheses and the network variables that affect the innovative performance of firms. Second, we provide a detailed description of the data, variables and methods we use to test our hypotheses. Third, we provide an overview of the most important results of our analyses using a longitudinal dataset covering technological activities, alliance strategies and financial data on the population of producers of ASICs (*application-specific integrated circuits*) in 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. In the last section we draw some conclusions and discuss the managerial implications of our main research findings.

3.2 Theory and Hypotheses.

Clique membership and innovative performance. While the performance consequences of embeddedness in firm-level ego networks and industry-level networks are increasingly understood, we know considerably less about the role of intermediate network structures that lie between the firm and industry level *(Dorian, 1992).* Prior research indicates that membership in these so-called implicit cliques does positively affect performance in industries such as health care *(Provan & Sebastian, 1998),* micro-processors *(Gomes-Casseres, 1996),* airline operations *(Lazzarini, 2007)* and investment banking *(Rowley et al., 2004).* Surprisingly almost no prior research focused on the main effects of clique-embeddedness on innovative performance.

A widely shared view within inter-firm concerns the positive effects of embeddedness on firm performance *(Uzzi, 1996).* Cliques are generally viewed as one of the most powerful sources of embeddedness since firms are mainly influenced by its most direct set of business partners. According to Lazzarini (*2007, p.346*) "clique-membership benefits stem from the possibility to internalize positive externalities emanating from the presence of other firms in the group". Clique externalities occur by knowledge spillovers facilitated by the strong and repeated interactions with stable partners within the clique. Especially within innovative and knowledge intensive industries, firms benefit from repeated interactions within dense network structures since these alliances are embedded within an atmosphere of trust. Trust has been identified as an essential element for alliance success, particularly in technological environments where trust is indispensable for knowledge sharing and joint learning *(Krishnan, Martin & Noorderhaven, 2006).* Trust facilitates a firm's willingness and ability to share information *(Ahuja, 2000b).* Hence, cohesive cliques facilitate the formation of trust and norms within a clique all of which facilitates learning and knowledge sharing which increases the innovative performance of clique-members vis-à-vis non clique-members. Other benefits that have been linked to clique membership relate to the faster pace at which knowledge is shared within cliques, knowledge reciprocity and redundancy which allows knowledge to be more meaningfully understood and the facilitation of economies of scale and scope *(Coleman, 1988; Burt, 1992; Gomes-Casseres, 1996).*

Firms that choose to adopt a non-clique strategy have fewer possibilities to take advantage of clique externalities and knowledge spillovers that stem from repeated and strong interactions between clique members. While peripheral firms that lack these embedded relations can outperform incumbents based on the radicalness or disruptiveness of their technologies *(Henderson & Clark, 1990; Mitchell, 1989),* we expect these peripheral firms to under-perform based on the relative sizes of their overall innovative performance. Firms embedded within clique's posses' access to larger amounts of information which is available at a shorter distance via direct or indirect contacts within their cliques. Hence, firms that are not in a position to benefit from these embedded relations that stimulate trust and knowledge spillovers have a less beneficial position within the alliance network. Therefore, we argue that clique members will be more innovative vis-à-vis non clique members.

Hypothesis 1: Clique members are more innovative compared to non clique members.

Position within the clique. While our last hypothesis states that clique-membership is beneficial, we expect that not all companies are able to benefit from their clique-membership equally. Prior findings indicate that variation between cliques, -i.e. differences between clique-characteristics- and variation within cliques, -i.e. differences between clique-members' attributes- affects the relation between clique-membership and performance *(Lazzarini, 2007; Rowley et al., 2004).* Variation is observable between cliques in the sense that historic alliance formation patterns carved unique structural, relational and positional features to each clique within the overall alliance network. For example, cliques vary in terms of the number of firms that are embedded within the clique, the density and strength of ties within the clique and the number of ties going beyond the scope of the clique. Variation is also observable within cliques in the sense that each firm brings in its own specific organizational attributes to the clique. For example, firms vary in terms of their size and resources, the function they play within the industry, and position they occupy within the overall alliance network. While prior studies provide valuable insights into the complex relationship between clique-membership and performance, we know relatively less about how network position *within the clique* affects performance. Under pressure of network endogenous and network exogenous forces each firm comes to occupy a unique position within the clique which influences their access to the resources, information and opportunities available within the clique. Therefore, we expect that the positive benefits of clique membership on performance are not distributed equally over all clique members and that various sources of heterogeneity can be distinguished between clique-members relative towards each other. The question in the next section is whether and how the expected relationship between clique-embeddedness and innovative performance is affected by the position of the firm within the clique. More in particular, we look at how companies' prominence, embeddedness and past alliance behavior within the clique affects its innovative performance.

Clique Prominence. Prominence deals with how visible or involved a firm is based on their position in the alliance network *(Knoke & Burt, 1983).* Firms that are more prominent (i.e. important) are located on strategic locations within the network, and hence more visible within the overall alliance network. To a large extent, visibility can be seen as a demonstration of reliability and accountability to potential alliance partners *(Hannan & Freeman, 1984, Podolny, 2001).* Prior research provided evidence for the beneficial relation between prominence in the overall alliance network and performance *(Koka & Prescott, 2008; Shipilov, 2005; Zaheer & Bell, 2005).* This positive relationship between network prominence and performance arise from two distinct mechanisms. On the one hand, prominence provides more access to key and valuable sources of information and on the other hand, prominence provides opportunities for firms' to establish its competitive and strategic agenda as the defining norm in the industry/network *(Koka & Prescott, 2008).* Since these studies all focus on the prominence of the firm within the overall network it remains unclear to what extent firm's benefit from prominent positions within the clique.

Clique benefits arise from knowledge spillovers facilitated by interactions with partners within the clique and we hypothesize that prominence in the clique is a significant predictor of innovative performance. This of course leads us to the question of what constitutes a prominent position in a clique, and how this can be described and measure. As prominence deals with how visible or involved a firm is based on their position in the alliance network *(Knoke & Burt, 1983),* prominence inside the clique deals with how visible or involved a firm is based on their position in the clique. Generally, firms become more visible and prominent in the alliance network if they occupy central positions, which allow them to be involved in a large amount of knowledge flowing in the alliance network *(Freeman, 1979).* Following this logic, firms become more visible and prominent in the clique if they occupy central positions inside the clique, allowing them to be involved in a large amount of knowledge flowing inside the clique. Hence, the extent to which a firm is able to know and control the interactions between their clique-members allows them to benefit from this prominent position in their clique *(Vanhaverbeke & Noorderhaven, 2001).* Therefore, we argue that a firm's prominence within the clique will allow a firm to grasp above average returns from the externalities of their clique-membership.

> *Hypothesis 2:* *Clique members that are more prominent in the clique are more innovative than clique members that are less prominent in the clique.*

Clique Embeddedness. While the last hypotheses relates to a firms position inside the scope of the clique, the relations a firm maintains beyond the scope of the clique should also be considered for its effect on a firm's innovative performance. Access to varied sources of knowledge and skills is an essential element for a firm's innovative capacity. However, within dense cliques knowledge bases start to become alike over time as interaction breeds attraction and similarity, thereby decreasing the novelty factor of information flowing within the clique *(Brass, Butterfield & Skaggs, 1998; Gilsing et al., 2008; Wuyts et al., 2005).* This so-called over-embeddedness diminishes the positive effects of clique-membership and leads to decreasing opportunities for learning and innovation for clique-members *(Hagedoorn & Frankfort, 2008; Duysters & Lemmens, 2003; Uzzi, 1997).* By maintaining ties beyond the scope of the clique a firm decreases its dependency on the internal knowledge flows and increases its autonomy and access to a more diverse set of partners and technological knowledge. Furthermore, these firms are able to separate non-redundant sources of information and have opportunities to broker the flow of information amongst otherwise unconnected (*groups of*) firms. Burt (*1992*) argues that the competitive advantage of firms rests on their ability to control knowledge flows between dense groups of firms. Firms lacking these so-called structural holes will benefit less from knowledge flowing in and out the clique since these firms have higher levels of redundant ties within the clique. Hence, firms maintaining ties inside as well as outside the clique can be considered to have access to multiple, disconnected knowledge pools, enabling less dependency on the cliques internal pool of knowledge. Contemporary research findings support evidence that a so-called hybrid network position, balancing ties within and between cliques, is beneficial for a firm's innovative performance *(Padula, 2008).* While this research indicates that having a large number of both ties within and between cliques is beneficial, we know relatively little about the optimal configuration of a firm's alliance portfolio relative towards one another.

An optimal network balances two sometimes conflicting forces as access to non-redundant partners forms a key source of novelty, whereas embeddedness in dense groups of firms is critical for realizing this potential *(Vanhaverbeke et al., 2008).* At the one extreme, firms may be fully embedded within the clique, whereby they have a very large dependency on the internal knowledge flows and have to rely on information with a lower novelty factor. At the other extreme, firms may be embedded within the clique, but only to a very small extent relative to the other ties it maintains in its alliance portfolio. However, given the fact that clique-members already benefit from the positive externalities of their clique-membership, we expect that firms that are capable of maintaining more non-redundant ties, relative to their overall ties, are able to benefit most from their clique-embeddedness. Therefore, we expect that the dependency of a firm within on knowledge flows within a single clique will be negatively related to the innovative output of the firm.

> *Hypothesis 3:* *Clique members that are less embedded in the clique are more innovative than clique members that are more embedded in the clique.*

Past alliance behavior. Whereas the last two hypotheses relate to a firms current position within the clique, we also argue that a firm's innovative performance is dependent on a firms strategic motivations underlying its past alliance behavior. Following our previous arguments, clique-members vary in terms of their position within and beyond the scope of their clique causing variation between companies in terms of their current access to sources of knowledge. On the one hand this variation is caused by a firm's own past alliance behavior, and on the other hand it is also the outcome of past alliance behavior of all firms within the clique. In this sense, the extent to which a firm is currently able to benefit from knowledge streams within the alliance network is contingent on its own actions but is also contingent on the actions of its partners and its partner's partner. While some of these actions by other firms might be favorable for a firms position, other actions might decrease a firms potential to access and control valuable sources of knowledge, which induces a focal firm to reposition themselves into new favorable positions. Since our last hypotheses are related to a firms current network positions, it remains unknown how firms' own past alliance behavior in terms of its strategic intentions influences its innovative performance. Therefore, in order to describe the full dynamics of the effects of a company's position within the clique on its innovative performance the past alliance behavior of these companies has to be taken into account in relation to its strategic intentions.

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*). While all these forms of network dynamics are interesting in its own right, here we focus on the formation of new ties of clique-members that bridge two distinct cliques. While insights in the rationale and mechanisms underlying new tie formation are increasing *(e.g. Ahuja, 2000a; Gulati, 1995a, 1995b; Gulati & Garguilo, 1999; Hagedoorn, 1993, 1996; Nohria & Garcia-Pont, 1991; Stuart, 1998, 2000),* there is only a handful of studies investigating the dynamic differentiation of ties in terms of their network structural properties relating to the clique *(Baum, Shipilov & Rowley, 2003; Rosenkopf & Padula, 2008).* By forming a clique spanning tie, firms maneuver themselves in a broker position by establishing a new tie to other central parts of the overall network. According to Baum, Shipilov & Rowley (*2003 p.704*) "firms in a broker position create information asymmetry between themselves and other firms, in such a way as to increase the dependence of other firms on them and to strengthen in this way their power in the network". Clique spanning ties can thus be expected to have positive rents for firms maneuvering themselves in a position as broker between two cliques. While most studies have shown motives why firms tend to be locally biased and path-dependent in their search strategies *(Gulati, 1995a; Stuart & Podolny, 2000; Walker, Kogut & Shan, 1997),* relatively less is known about the performance implication of firms past alliance actions in which firms opt for forming a clique spanning tie.

Since clique-members are already embedded within structures that enable them to benefit from these embedded relations, we expect that clique members that established relatively more clique spanning ties in the past will be more innovative. Clique spanning ties provide access to different sources of knowledge which is considered as an important factor for innovation. By forming a clique spanning tie firms reach beyond their existing technological knowledge pools in search for more non-redundant sources of information. While these arguments all point out a positive relationship between the formation of clique spanning ties and innovative performance other research findings caution for the negative aspects. Access to novel sources of contacts and knowledge is time-consuming and firms are limited in the amount of knowledge they can absorb *(Cohen & Levinthal 1990).* The benefits of access to more sources of unrelated or novel sources of knowledge may be limited and the cost of maintaining these ties comes with a price. There is a limit to the number of ties can manage successfully *(Gomes-Casseres, 1996)* and larger technology alliance portfolio's increases the risks of dealing with various, often unfamiliar streams of knowledge that are increasingly difficult to integrate *(Grandstrand, Oskarsson & Sjoberg, 1992, Ahuja, & Katila, 2004; Vanhaverbeke et al., 2008)*. Based on these arguments we expect to find a positive linear and an inverted U-shaped relationship between a firm's prior alliance behavior and its technological portfolio. An increase in the number of clique spanning ties leads to reduced marginal benefits and effectiveness of adding additional ties.

Hypothesis 4: *Clique members that established more clique spanning ties in the past are more innovative.*

Hypothesis 5: *Clique members that established more clique spanning ties in the past are more innovative but this relation is an inverted U-shape.*

3.3 Data, Variables and Modeling.

Data. We constructed a panel dataset that covers the population of ASIC producers over the period 1987-2000. This period captures an important period in the technological development of the ASIC-Industry. Based on the vendor-list included in the ICE ASIC-Outlook industry reports (*McClean, 1987-2000*) we were able to establish a detailed list of all ASIC-producers. The measures of the technological knowledge bases draw on patent data from the US Patent and Trademark Office[8]. In particular in industries where companies operate on a global scale, such as the ASIC-industry, U.S. patents are a good proxy for companies' worldwide technological performance and technological assets. The data on strategic technology alliances were obtained from the ICE-industry reports; the ASIC-Outlook reports (*McClean, 1977-2000*) and the MERIT-CATI database on strategic technology alliances *(Hagedoorn, 1993).* Financial data of ASIC producers have been gathered from different sources among which the annual *ICE reports* (*McClean, 1977-2000*) and COMPUSTAT.

Dependent Variable. Our dependent variable is a measure the technological performance of firms active on the ASIC-industry. We measured technological performance by the number of patents that a company successfully applied[9] for in a particular year, weighted by the citations it received afterwards. 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, 2000a; Stuart, 2000; Hagedoorn & Duysters, 2002; Schilling & Phelps, 2007).* We weighted patents by the citations they received afterwards 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 and 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 by Hall, Jaffe & Trajtenberg (*2001*).

Independent Variables. The first independent variable clique membership indicates whether firms are embedded within a clique or not. In line with prior research on cliques *(Rowley et al., 2005),* we used the N-Clan procedure

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[8] 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*).

[9] 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.

implemented in UCINET to detect relevant cliques *(Borgatti, Everett & Freeman, 1999).* The N-Clan procedure allows firms to be embedded in more than one clique and detects cliques based on a predefined maximum distance between all firm in the clique and a predefined minimal size of the clique. By using a maximum distance of 2 we assured that firms in the same clique were either connected by a direct tie or were connected by an indirect tie. By using a minimal group size of 5 members we assured that cliques had a significant size to detect variations across cliques in terms of their internal and external linkages.

Definitions of prominence, or synonymously, importance, have been offered by many writers. These measures attempt to describe and measure properties of "actor location" in a social network *(Wasserman & Faust, 1994; p.169).* Various measures of prominence have been used within social network literature such as, betweenness centrality *(Freeman, 1979),* power *(Bonacich, 1987)* and autonomy *(Burt, 1992).* Since these classical measures focus on the prominence of the firm within the overall network these measures were not suitable to measure the prominence of the firm within the clique. Therefore we constructed a measure for clique prominence which indicates how prominent a firm is within a certain clique. We calculated this measure *clique-prominence* based on the total number of ties firm $_i$ has inside clique $_j$ and divide that number by the total number of inside ties of all firms embedded within clique $_j$. Theoretical, this measure can range between 0 and 1, higher values indicating higher levels of prominence within the clique.

By maintaining a balanced set of ties within and beyond the scope of the clique firms can minimize their dependency on knowledge flowing inside the clique. This dependency can be calculated as a simple count of the number of alliances a firm $_i$ maintains inside and outside clique $_j$. However, a ratio of a firm's inside and outside ties is a more precise indication of a firm's dependency on knowledge flowing inside the clique, since a relative measure controls for the relative sizes of each of these particular types of ties. The EI-Index is such a relative measure, designed to calculate a firm's tendency to maintain ties that can be considered as external and internal clique relationships *(Krackhardt & Stern, 1988).* This normalized measure ranges from *-1*, indicating that firm $_i$ is fully embedded in its clique $_j$ because all ties were internal clique relationships, to *+1* indicating that a firm maintains only ties external to the clique. [10]

While our last two variables were constructed based on the network position a firm maintained one year prior to the observation year, we build our hypothesis on prior clique spanning ties around the strategic intentions of a firm past

[10] We multiplied the original measures of the EI-calculations by -1, such that higher values represent a higher level of embeddedness.

alliance behavior 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).* Regarding the strategic intentions of a firm past alliance behavior we are interested in the strategic intentions of all new ties that a firm formed within the 5 years prior to the observation year. The strategic intentions of clique-members new tie formation can be classified into "inside clique ties", "outside clique ties with peripheral network members" and "clique spanning ties". 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 can then be measured by counting the number of clique spanning ties that a firm initiated 5 years prior to the observation year.

Control Variables. We included four organizational variables, two clique variables, and four dummy variables to control for unobserved effects. To control for unobserved heterogeneity at the firm level we included the variable 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).* The second firm-level variable relates to the centrality of a firm in the overall alliance network. Being located in the center of an alliance network has been recognized as an important and distinctive form of social capital of innovating firms *(Gulati, 1995a; 1999).* To measure centrality we used the measure of eigenvector centrality *(Bonacich, 1972).* Eigenvector centrality is a measure of the importance of a firm in the alliance network. It assigns relative scores to all firms in the network based on the principal that connections to high-central firms is more important than connections to firms that are less central.

The third firm-level variable relates to the size of the firm. Large firms have a broader and more diversified established network of alliances *(Hagedoorn & Duijsters, 2002)* and place themselves as dominant firms not only within the clique but also in the overall alliance network. Due to their size benefit, large firms are more likely to be profit from economies of scale and scope and thereby they have a higher potential to increase their technological performance over time. We calculated this variable based on the natural logarithm of a firm's annual sales. The fourth firm-level control 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. We calculated this variable based on the R&D to sales ratio of each firm.

Furthermore, we include four types of dummy variables to control for different types of contingencies. A first dummy variable was included to control for a potential bias as some large companies produce ASICs only for their internal needs. 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*). Second, industry dummy variables were included to indicate the industry to which an ASIC-producer belongs. 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 third 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 3 provides a detailed overview of all measures that have been used within the empirical analysis.

Modeling. To test our hypothesis a longitudinal panel data set has been set up for the purpose of this study. Panel data, or cross-sectional time series data, are data where each company is observed over more than two time periods. Observing changes in the independent as well as the dependent variable allows for determining causal effects between two variables. Using standard multivariate regression techniques on a panel data-set is less reliable as it is unable to derive reliable estimates due to omitted variable bias (*Baltagi, 2005*). Panel data regression techniques are able to observe changes in the dependent as well as the independent variable for these omitted variables that either varies over time or between cases (*one of these two factors needs to be constant*). For panel data where the dependent variable is a count variable, such as the dependent variable within this study -i.e. weighted patent count-, a Poisson regression approach provides a natural baseline model (*Hausman, Hall & Grilliches., 1984; Henderson & Cockburn, 1996*). However, a Poisson regression assumes that the mean and variance of the count distribution are equal, and in particular for panel data this assumption is likely to be violated. Because our data does indeed show evidence of over-dispersion a negative binomial regression model is most appropriate *(Cameron & Trivedi, 1998),* since this estimation procedure allows the variance to exceed the mean (*Hausman, Hall & Grilliches, 1984*). Negative binomial regression is a nonlinear regression technique, estimated by either maximum likelihood, or as a generalized linear model (*Hilbe, 2007*). To avoid potential specification errors it is necessary to control for unobserved heterogeneity (*Heckman, 1979*). Unobserved heterogeneity here refers to the possibility that unmeasured differences among observationally equivalent firms affect their innovative performance, which has been measured as weighted patent counts. Unobserved heterogeneity may also be the result of systematic time period and industry effects.

Using the negative binomial model in panel data implies that unobserved effects of individual firms are controlled for either through fixed or random effects. To determine the choice between a random-effect and fixed-effect model we conducted a Hausman test (*1978*). The Hausman test tests the null hypothesis that the coefficients estimated by a random effects estimator are the same as the coefficients by the fixed effects estimator. The Hausman test indicated a significant p-value which means that a fixed effects model is the appropriate model for this analysis. As fixed effects estimators depend on deviations from the mean, these estimators are referred to as within-group estimators.

3.4 Results.
In table 4 we present the descriptive statistics and the correlation matrix for the different variables. Table 5 shows the results of the fixed effects negative binomial regression analyses for the 517 observations in the sample.

We find support for hypothesis 1, which examined the effects of clique-membership on firm innovative performance. The estimates in this model show that clique-membership is positively and significantly related to innovative performance. Firms that are embedded within densely connected cliques are on average more innovative (*weighted patent counts*) than firms that are not embedded within densely connected cliques. Regarding our other hypotheses we concentrate on the full model (*model 7*), but we also display the model with only the control variables (*model 2*) and models that add in a stepwise way different explanatory variables (*models 3-6*). These models demonstrate that the estimates of the coefficients of the main effects are robust over the various models and that multicollinearity is not a particular problem in these regressions. All models show significant improvements over the baseline model indicating that including the main effects add explanatory power to the model. In hypotheses 2 we predicted a positive effect of prominence within the clique on innovative performance. This hypothesis is strongly supported indicating that in addition to a firm’s position in the overall network, a firm’s position within the clique also contributes to a firm’s innovative performance. Hypothesis 3 finds a positive effect of a firm’s embeddedness within the clique on innovative performance.

Table 3: Definition of dependent and independent variables.

Variable name	Variable description
Innovative performance	Count variable indicating the number of successful patent applications, weighted by the number of citations they receive.
Clique membership	Dichotomized variable (0/1) indicating if a firm is a clique member in alliance network $_{(t1\text{-}5)}$
Clique Prominence	Ratio calculated as the total inside ties of firm i in clique j divided by the total inside ties of clique j. $_{(t1\text{-}5)}$
Clique Embeddedness	Normalized measure of the ratio between internal and external relationships $_{(t1\text{-}5)}$
Past clique spanning ties	Prior ties that a firm formed that brokered two different cliques $_{(t1\text{-}5)}$
Past clique spanning ties²	Prior ties that a firm formed that brokered two different cliques $_{(t1\text{-}5)}$
Technological Capital	Count variable indicating the number of successful patent applications in $_{(t1\text{-}5)}$
Social Capital	Eigenvector Centrality (Bonacich, 1972)
Firm Size	Total overall sales of the focal firm/1000 $_{(t1)}$
Firm R&D	Firm total R&D expenditures / Firm overall sales $_{(t1)}$
Captive producer	Dummy variable denoting that the firm is not selling products on the ASIC-market
SC Producer	Dummy variable denoting that the firm is producing only Standard Cells
PLD Producer	Dummy variable denoting that the firm is producing only PLDs
GA-SC Producer	Dummy variable denoting that the firm is producing only Gate Arrays and Standard Cells
GA-PLD Producer	Dummy variable denoting that the firm is producing only Gate Arrays and PLDs
SC-PLD Producer	Dummy variable denoting that the firm is producing only Standard Cells and PLDs
GA-SC-PLD Producer	Dummy variable denoting that the firm is producing Gate Arrays and Standard Cells and PLDs
European Firm	Dummy variable denoting that the firm is headquartered in Europe
Asian Firm	Dummy variable denoting that the firm is headquartered in Asia
Dummy 1988-2000	Dummy variable denoting the year of observation

Table 4: Descriptive statistics and correlation matrix.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Innov. Perf.	1.00																
2	Clique Prom.	0.13	1.00															
3	Clique Emb.	0.10	0.09	1.00														
4	Past alliances	0.08	0.22	0.50	1.00													
5	Techn. Cap.	0.73	0.17	0.19	0.21	1.00												
6	Social Cap.	-0.09	0.01	0.42	0.49	-0.02	1.00											
7	Firm Size	-0.11	-0.10	0.10	0.16	0.00	0.15	1.00										
8	Firm R&D	0.08	0.04	-0.07	-0.07	0.01	-0.09	-0.43	1.00									
9	Captive	-0.13	-0.23	-0.23	-0.12	-0.15	-0.02	0.19	-0.17	1.00								
10	GA	-0.07	-0.17	-0.13	-0.12	-0.10	-0.11	-0.02	0.16	0.02	1.00							
11	PLD	-0.11	-0.13	-0.28	-0.14	-0.16	-0.11	0.03	0.07	0.36	-0.11	1.00						
12	GA-PLD	-0.20	-0.01	0.06	0.06	-0.11	0.00	0.20	-0.37	0.00	-0.20	-0.42	1.00					
13	SC-PLD	-0.02	0.03	0.10	0.09	-0.03	0.14	-0.07	0.04	-0.06	-0.03	-0.06	-0.11	1.00				
14	GA-PLD	0.02	0.15	0.01	-0.02	0.04	0.01	-0.02	0.06	-0.07	-0.04	-0.08	-0.15	-0.02	1.00			
15	GA-SC-PLD	-0.05	0.17	030	0.24	0.01	0.36	0.02	-0.08	-0.18	-0.09	-0.19	-0.36	-0.05	-0.07	1.00		
16	European	-0.14	-0.10	0.06	0.02	-0.17	0.48	0.04	-0.03	0.14	-0.05	0.08	-0.01	-0.06	0.11	0.12	1.00	
17	Asian	-0.14	-0.18	-0.06	-0.10	-0.05	-0.19	0.23	-0.42	-0.13	-0.06	-0.24	0.52	-0.07	-0.10	-0.19	-0.28	1.00
	Mean	144.1	0.14	0.19	1.21	15.62	13.91	1.80	0.11	0.16	0.48	0.18	0.44	0.15	0.27	0.14	0.17	0.27
	Standard D.	373.5	0.85	0.46	1.23	27.21	15.10	2.43	0.07	0.37	0.21	0.39	0.50	0.12	0.16	0.35	0.38	0.45
	Minimum	0.00	0.02	-0.54	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Maximum	3791	0.50	1.00	8.00	307	66.91	16.41	0.67	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 5: Fixed effects panel estimation results for Innovative performance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Clique-memb.	0.60 (0.14)***						
Clique Prom.			2.48 (0.53)***				2.73 (0.65)***
Clique Emb.				-0.50 (0.15)***			-0.48 (0.17)***
Past alliances					0.27 (0.05)***	0.49 (0.09)***	0.35 (0.10)***
Past alliances²						-0.05 (0.02)***	-0.03 (0.02)**
Techn. Capital	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***
Social Capital	0.02 (0.00)***	0.01 (0.00)***	0.02 (0.00)***	0.01 (0.00)**	-0.00 (0.01)	0.00 (0.01)	0.01 (0.01)
Firm Size	0.10 (0.03)***	0.08 (0.03)**	0.08 (0.03)**	0.07 (0.03)**	0.06 (0.03)*	0.08 (0.04)**	0.07 (0.04)**
Firm R&D	-0.08 (0.86)	-0.31 (1.24)	0.09 (1.24)	-0.50 (1.27)	-0.33 (1.23)	-0.60 (1.25)	-0.31 (1.27)
Captive	-0.10 (0.20)	-0.06 (0.24)	0.01 (0.24)	0.03 (0.23)	0.15 (0.23)	0.10 (0.24)	0.21 (0.24)
GA	-1.50 (0.31)***	-1.35 (0.48)***	-1.34 (0.49)***	-1.41 (0.48)***	-1.49 (0.48)***	-1.46 (0.48)***	-1.49 (0.49)***
SC	-1.78 (0.26)***	-1.54 (0.31)***	-1.62 (0.31)***	-1.52 (0.31)***	-1.79 (0.31)***	-1.68 (0.32)***	-1.71 (0.31)***
GA-SC	-1.05 (0.22)***	-0.97 (0.25)***	-1.16 (0.25)***	-1.06 (0.25)***	-1.11 (0.25)***	-1.20 (0.25)***	-1.42 (0.25)***
SC-PLD.	-0.42 (0.47)	-0.51 (0.48)	-0.71 (0.48)	-0.67 (0.48)	-0.28 (0.47)	-0.59 (0.48)	-0.91 (0.49)*
GA-PLD	0.66 (0.28)**	0.60 (0.30)**	0.35 (0.29)	0.60 (0.30)**	0.61 (0.29)**	0.58 (0.29)**	0.35 (0.28)
GA-SC-PLD	-0.73 (0.24)***	-0.50 (0.27)*	-0.72 (0.27)***	-0.64 (0.27)**	-0.49 (0.27)*	-0.62 (0.27)**	-0.94 (0.28)***
European	-0.58 (0.22)***	-0.81 (0.24)***	-0.76 (0.24)***	-0.80 (0.24)***	-0.68 (0.23)***	-0.81 (0.24)***	-0.73 (0.24)***
Asian	0.30 (0.18)	0.27 (0.22)	0.47 (0.22)**	0.29 (0.22)	0.33 (0.22)	0.28 (0.22)	0.52 (0.23)**
Constant-year	Included	Included	Included	Included	Included	Included	Included
Obs. (firms)	848 (71)	517 (51)	517 (51)	517 (51)	517 (51)	517 (51)	517 (51)
Log Likelihood	2575,39	2019,99	2010,54	2013,75	2004,28	2000,42	1990,99
Lr-test	10,19***		9,45***	6,24***	15,71***	19,57***	29***

Table shows results of fixed effects negative binomial model
Note 1: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$
Note 2: Standard Deviations in Parentheses

Clique-members that are able to maintain alliance beyond the scope of the clique are able to benefit from their access to these non-redundant streams of technological knowledge. This result further supports the idea that a firm's position within the clique contributes to a firm's innovative performance. Both a firm's prominence within the clique (*hypothesis 2*) and a firm's embeddedness within the clique contribute to a firm's innovative performance.

In hypotheses 4 and 5 we examined the effects of firm's prior network actions that intended to position the firm as a bridge between two cliques. The positive sign indicates that a firm's prior network actions beyond the scope of the clique do indeed contribute to the innovative performance of a firm. Establishing clique spanning ties is a positive and significant contributor to innovative performance, but the negative sign for the quadratic term indicates that the relation between establishing clique spanning ties and innovative performance has an inverse U-shape relationship. Firms that establish low and high amounts of ties between cliques perform less than firms with a more mediate number of these ties.

3.5 Discussion and Conclusions.

This paper aims to improve our understanding of how firms position themselves in alliance networks in order to foster their innovative performance. While most studies investigated the effects of network position from the perspective of the ego- or overall network, we follow the limited studies that draw attention to the relationship between clique-embeddedness and innovative performance *(Padula, 2008).* We expect that clique embeddedness has a positive effect on innovative performance, but expect that these benefits are not distributed equally over all clique members as some firms are better positioned to take advantage of the clique benefits. Our findings support the notion that clique-membership provide positive externalities in such a way that the embedded firms are able to benefit by significant increases in their innovative performance. Innovation is positively influenced by the knowledge spillovers that occur via the strong and repeated interactions between clique-members. These findings clearly indicate that not only to the ego-level and network-level play an important role for a firms innovative capacity and supports the importance of further studying the performance effects of cliques *(Lazzarini, 2007; Padula, 2008; Rowley et al., 2004).* Our results also indicate that not all that glitters is gold for members of cliques. Significant variations in a firms potential to benefit from their clique-embeddedness stem from their position within the clique. The internal structure of the clique clearly indicates a scenario in which the most prominent firms inside the clique claim the most benefits. Furthermore, being less embedded within the clique further stimulates a firm's innovative performance as access to non-redundant partner's forms a key source of novelty, supplementing the already assured benefits from clique-embeddedness.

The current study also has several directions for future research. Our results clearly indicate that clique-membership positively affects a firm's innovative performance but these effects might diminish under periods of significant technological change. Under these periods, non-clique members could outperform clique-members as they can maneuver more flexible into new technological opportunities without facing the inertia that clique-members face *(Madhavan, Koka & Prescott, 1998; Koka & Prescott, 2008; Uzzi, 1997).* Furthermore, while we were able to show that not all clique-members benefit equally caused by variations between firms position inside the clique, other sources of variation might also play a role here. Other variations might stem from differences between firm's attributes such as their technological portfolio's or stem from differences between clique attributes such as the age, size, density or technological similarities of the clique. Another path for future research is to investigate the different forms of ties that clique members form -i.e. "inside clique ties", "outside clique ties with peripheral network members" and "clique spanning ties"- and to investigate the effects on innovative performance. For example, while the formation of a new inside clique tie might be related to the creation of new exploitative innovations, the formation of clique spanning ties might be related to the creation of explorative innovations.

This study was limited to a technique that detected overlapping cliques. A firms position inside the 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, Shipilov & Rowley, 2003*). The clique is however gaining momentum in the managerial literature with a potential to link multiple levels of analysis in the network literature *(Baum, Shipilov & Rowley, 2003; Lazzarini, 2007; Padula, 2008; Rosenkopf & Padula, 2008; Rowley et al., 2004; 2005).* Our results indicate that clique-membership does enhance a firm's innovative performance, but that not all that glitters is gold for all members of the clique. Significant variations arise from a firms position inside the clique and from its past alliance behavior.

Chapter 4: Mind the Gap

Balancing alliance network and technological portfolios during periods of technological uncertainty

Abstract

Despite several recent advancements there is still a lack of insight regarding the dynamic aspects of clique-embeddedness. 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. One of these exceptions which could affect the effectiveness of clique-embeddedness is when technological change makes existing knowledge bases obsolete. In order to gain a deeper insight into the effect of technological uncertainty on the effectiveness of clique-embeddedness, we investigated various underlying mechanisms of clique-embeddedness which become relevant during periods of technological uncertainty: the opportunity to access novel sources of technological knowledge within the clique and the ability to adapt during these periods. We found support for the notion that knowledge bases within cliques are more similar than across cliques but our results did not indicate that clique-membership is less beneficial during periods of technological uncertainty. However, while the formation of past inside clique ties did not affect a firms innovative performance during technological turbulent periods, the formation of past clique spanning ties did in fact positively influence a firms innovative performance during technological turbulent periods.

Keywords: alliance networks; clique membership; technology profiles; innovative performance

4.1 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; Meeus, Oerlemans & Kenis, 2008; Pittaway et al., 2004)*. Consequently, embeddedness within a well functioning web of partners has become an essential element for a firm's technological performance. Yet, while embeddedness in technology-based alliances networks should allow all companies to enhance their innovative performance, empirical evidence also indicates that not all companies are able to enhance its innovative performance equally. The effectiveness of embeddedness in technology-based alliances has been ascribed to two underlying mechanisms: the opportunity to access valuable technological knowledge and the opportunity to control the knowledge and technologies flowing in the alliance network *(Coleman, 1988; Burt, 1992).* Hence, in order to analyze the effectiveness of embeddedness in technology-based alliances a complete picture of the whole network is needed since firms' position in the overall alliance network and the type of alliances they maintain defines its access to, and control over, those opportunities *(Gulati, 1998; Uzzi, 1996).* While the factors that mediate the effectiveness of embeddedness in technology-based alliances are increasingly well understood from the perspective of firm-level ego networks *(Ahuja, 2000a; Baum, Calabrese, Silverman, 2000; Hagedoorn & Schakenraad, 1994; Owen-Smith & Powell, 2004; Rothaermel & Deeds, 2006; Shan, Walker & Kogut, 1994; Stuart, 2000)* and industry-level networks *(Rowley et al., 2000; Schilling & Phelps, 2007)*, there is still a shortage of studies that examine the effectiveness of technology based alliance networks from the perspective of the clique, i.e. intermediate network substructures that lie in between the ego-network level and industry-network level *(Dorian, 1992; Rowley et al., 2004).*

Studying cliques will enable us to refine the question why some networks and positions provide greater benefit to their members than others *(Lazzarini, 2007; Padula, 2008; Rowley et al., 2004).* Cliques 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)*. Cliques are generally viewed as one of the most powerful sources of embeddedness and past clique-studies did find positive effects of clique-membership on financial, operational and innovative performance *(Lazzarini, 2007; Rowley et al., 2004).* While clique-embeddedness is generally considered to enhance innovative performance, there are however reasons to expect that under some circumstances clique-membership is less beneficial or might even become a liability. We argue that the effectiveness of clique-embeddedness is contingent on the needs of the external environment in which the firm is competing (*Burt, 2000; Lawrence & Lorch, 1967; Rowley, Behrens & Krackhardt, 2000*) and on firms' ability to adapt to changing conditions in the external environment.

One of these conditions in the external environment is when technological changes make existing knowledge bases obsolete. During these changes, clique-members are not necessarily in a beneficial position as radical *(Leifer et al., 2000)* and potentially disruptive new technologies *(Christensen, 1997; Christensen & Raynor, 2003)* may originate in peripheral companies that challenge market leaders. Consequently, clique-membership could become a serious threat during these periods as firms need to explore new knowledge and technologies while the knowledge and technologies inside the clique are not capable of facilitating this process. Hence, technological uncertainty represents serious discontinuities for clique-members forcing them to establish new alliances in order to cope with the changing needs of the external environments. Different authors already provided evidence that technological shifts can be a reason for (re)structuring network structures when firms are searching to get access to the latest technological developments *(Barley, 1986; Burkhardt & Brass, 1990; Glasmeier, 1991; Lambe & Spekman, 1997; Madhavan, Koka & Prescott, 1998; Soh & Roberts, 2003).*

However, theories of network evolution state that network endogenous forces lead to durable and self-reproducing network positions, as firm behavior increases the likelihood of repeated ties among the already embedded firms *(Baum, Shipilov & Rowley, 2003; Gulati, 1995a, 1995b; Gulati & Garguilo, 1999; Powell et al., 2002).* This desire to keep existing relationships going is even more pronounced in highly redundant and dense networks since group pressures force firms to conform their new partnering behavior not to harm group norms. Hence, dynamics that are endogenous to the network lead firms to over-emphasize their involvement with the same set of partners through which they could become over-embedded within the clique *(Hagedoorn & Frankort, 2008; Duysters & Lemmens, 2003; Uzzi, 1997)*. Over-embeddedness generates decreasing opportunities for learning and innovation because the knowledge bases of intensively cooperating firms have the tendency to become more similar over time *(Brass, Butterfield & Skaggs, 1998; Mowery, Oxley & Silverman, 1996; Nooteboom, 2000; Wuyts, 2005).* This decreases the heterogeneity of technological knowledge inside the clique, which is a prerequisite for novel combinations to emerge *(Nooteboom, 2004; Schumpeter, 1939).* While a certain overlap in knowledge portfolios is a desirable aspect for the exploitation of existing knowledge and technologies, it is a serious threat for firms intending to explore beyond their existing areas of expertise *(March, 1991).* Hence, if knowledge and technologies inside cliques are indeed more similar to technological knowledge available outside the clique, the overembeddedness perspective might help to explain why companies reposition themselves beyond clique boundaries. Despite the arguments mentioned above, there still is a lack of insight in the dynamic aspects of clique-embeddedness while insight into these mechanisms is essential in order to fully explain how alliance networks emerge and evolve over time and how these network dynamics influence the innovative performance of the embedded firms.

This study will explore whether technological knowledge is indeed more similar inside the clique than beyond clique boundaries, which could assist understanding why companies reposition themselves beyond the boundaries of their clique, despite the general view that network endogenous forces lead to durable and self-reproducing network positions. This will enable us to further explore whether the effectiveness of clique-embeddedness is contingent on the needs of the external environment in which companies are competing, and whether the ability to adapt to changing conditions can explain the effectiveness of clique-embeddedness. This paper is organized as follows. First, we develop a set of hypotheses regarding the similarity of knowledge and technologies inside the clique and on how technological uncertainty and companies' ability to adapt may affect the innovative performance of firms. Second, we provide a detailed description of the data, variables and methods we use to test the hypotheses. Third, we give 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. In the last section we draw several conclusions and discuss the managerial implications of the main research findings.

4.2 Theory and Hypotheses.

Cliques: Knowledge similarity and innovative performance. Generally clique-membership is viewed as a very powerful tool to increase innovative performance. According to Lazzarini (*2007, p.346*) "clique-membership benefits stem from the possibility to internalize positive externalities emanating from the presence of other firms in the group". Strong and repeated interactions with a stable set of partners enables the development of shared behavior, group norms and trust. These mechanisms allow clique-members to pool and transfer (explicit) knowledge and technologies more deeply and at a higher pace *(Uzzi, 1997; Walker et al., 1997).* While prior empirical observations indicate that there 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.

Scholars argue that the accessible knowledge and technologies inside the clique is tends to be more similar to a companies own knowledge and technologies than the knowledge and technologies that are accessible outside the clique *(Brass, Butterfiel & Skaggs, 1998).* While some technological knowledge overlap inside the clique enables firms to improve its innovative performance initially, it might become a serious liability for these clique-members over time, e.g. close and intense relationships between clique-members could generate decreasing opportunities for learning and innovation as companies become over-embedded inside their clique *(Hagedoorn & Frankort, 2008; Uzzi, 1997)*. Over-embeddedness emanates as companies reach a certain threshold in technological overlap where adding additional partnerships generate decreasing opportunities for learning and innovation *(Hagedoorn & Frankort, 2008; Nooteboom, 2000; Uzzi, 1997).* Hence, over-embeddedness has implications for clique-members as the potential for finding useful new partnerships that generate new knowledge declines within their existing group of firms *(Duysters & Lemmens, 2003; Kenis & Knoke, 2002).*

While the arguments above indicate that clique-members should be careful not to become over-embedded within their clique, no prior studies empirically tested whether technological knowledge is indeed more similar inside the clique than beyond the clique. Two mechanisms help understand why a positive effect of joint clique-membership on similarity of technological knowledge could be expected. The first mechanism relates to the cooperation between clique-members themselves as companies learn from the knowledge and technologies of their alliance partners and internalize their partners' knowledge and technologies. Over time, due to their cooperation these companies become more similar over time *(Mowery, Oxley & Silverman, 1996)*, which should also be observable when companies are embedded within the same clique. The second mechanism relates to how companies choose their alliance partner as scholars argued that companies have a tendency to attract companies with some degree of technological overlap *(Brass, Butterfield & Skaggs, 1998).* Consequently, similarity breeds attraction as some degree of mutual understanding supports cooperating companies to pool and transfer technological knowledge and technologies more deeply and at a higher pace *(Brass, Butterfield & Skaggs, 1998; Gomes-Casseres, Hagedoorn & Jaffe, 2006).* For these reasons we expect knowledge bases of clique-members to be more similar than knowledge bases of companies embedded in different cliques.

Finding a positive effect for joint clique-membership on knowledge and technological similarity gives companies a clear incentive to reposition themselves beyond the boundaries of their clique in order to obtain new technological knowledge. Moreover, while these findings increase our understanding about knowledge and technological similarities inside and beyond the clique, it does not provide indisputable evidence that a repositioning strategy outside clique-boundaries does indeed connect a company to knowledge that is novel to its current knowledge base. Therefore, we posit an additional hypothesis that investigates whether forming an alliance beyond clique boundaries does indeed connect companies to novel technological knowledge.

Hypothesis 1: *The knowledge similarity between companies embedded in the same clique is larger than that of companies embedded in different cliques.*

Hypothesis 2: *The formation of a new technology-based alliance with a company embedded in the same clique provides access to knowledge that is more similar to companies own knowledge base than the formation of a new technology-based alliance with a company embedded within another clique.*

The argumentation presented above implies that clique members have a clear incentive to establish as much clique spanning ties as possible since these alliances provide clique-members with access to novel sources of technological knowledge. However, learning from novel sources of technological knowledge also has limitations as companies are limited in the amount of knowledge they can absorb *(Cohen & Levinthal 1990).* Hence, the benefits of access to higher amounts of novel sources of knowledge may be limited and might even come with a price given that larger technology alliance portfolio's increases the risks of dealing with more diverse and unfamiliar streams of knowledge and technologies that are increasingly difficult to integrate *(Grandstrand, Oskarsson & Sjoberg, 1992, Ahuja, & Katila, 2001; Vanhaverbeke et al., 2008).* Furthermore, clique spanning ties could have the other problems as companies are unable to absorb knowledge that is too distant from their current knowledge base *(Nooteboom et al., 2007).* Still, despite these potential dangers of too much outside clique ties, the formation of clique spanning ties should be beneficial for the innovative performance of clique-members.

While this indicates that forming high amounts of either inside or outside clique ties is not necessarily beneficial, it does not provide any information about the relative merits of establishing an alliance within or beyond clique boundaries. We argue that both the formation of a new inside clique tie as well as the formation of a new clique spanning tie contribute to the innovative performance of clique-members, since research indicates that having more ties increases companies' innovative performance *(Ahuja, 2000a; Hagedoorn & Schakenraad, 1994; Shan, Walker & Kogut, 1994; Stuart, 2000).* However, when comparing both types of ties, we expect that the formation of clique spanning ties will contribute more to the innovative performance of clique members than the formation of additional inside ties. The formation of clique spanning ties requires the allocation of higher amounts of resources and managerial time compared with the formation of inside clique ties since assimilating and integrating technological knowledge that is more novel to firms' current knowledge base is complex and time-consuming. Together, these factors should allow clique-members to improve their innovative performance as compared to the formation of additional inside clique ties.

> *Hypothesis 3:* *There is a positive effect between clique spanning ties as well as inside clique ties on innovative performance, but the effect of clique spanning ties is larger in effect.*

Cliques: technological uncertainty and innovative performance. While Clique embeddedness is generally considered to have a positive effect on performance *(Rowley et al., 2004; Lazzarini, 2007)*, there are also reasons to expect that not all clique-members are able to benefit from their clique-membership under all external conditions. One of the exceptions that could influence the effectiveness of clique-embeddedness is when technological change makes existing knowledge bases obsolete. During these shifts, clique-members are not necessarily in a beneficial position as radical *(Leifer et al., 2000)* and potentially disruptive new technologies *(Christensen, 1997; Christensen & Raynor, 2003)* originate in many cases in peripheral companies that challenge market leaders. Particularly within high-tech industries, technology shifts are a constant threat to incumbents' technological knowledge base. During these technology shifts companies have difficulty predicting the future *(Beckman, Haunschild & Phillips, 2004)*, making it very difficult to know what technological knowledge they have to invest in for future technological and commercial success *(Koka & Prescott, 2008)*. Hence, while stable environments emphasize the importance of network positions that enable exploitation of current knowledge and technologies, turbulent periods require network positions that facilitate exploration of new knowledge and technologies *(Burt, 2000; Rowley et al., 2000).* Consequently, clique-embeddedness might not be beneficial during these periods since the accessible knowledge and technologies inside the clique is not appropriate for the exploration of new knowledge and technologies. This observation was confirmed by the study of Rowley et al., (*2000*) which reported that dense alliance networks are a liability for companies embedded within turbulent technological environments. Hence, while it has been accepted that clique-embeddedness generally has a positive effect on a firms' innovative performance *(Lazzarini, 2007; Rowley et al., 2004)*, we argue that this relation depends on the technological uncertainty characterizing an industry at a particular point in time. It is expected that clique-embeddedness will be beneficial for companies in technological stable periods, in which incumbents can accumulate technological knowledge through well-defined technological trajectories. However, clique-embeddedness may become a liability during periods of technological uncertainty as the knowledge pool to which clique-members have access consists for a large extent of technological knowledge that is valuable given the non-accumulative and potential disruptive technologies that emerge during these periods. Therefore, we expect to find a negative effect of technological uncertainty on the innovative performance of clique members.

Hypothesis 4: Technological uncertainty has a negative effect on the innovative performance of clique members.

Especially within technological turbulent environments companies are constantly challenged to improve their learning capabilities and knowledge *(Cohen & Levinthal, 1989; March, 1991).* One way to cope with the uncertainties during technological uncertain periods is to establish alliances with complementary partners *(Hagedoorn, 1993).* Many studies observed changes in the composition of the alliance network during technological turbulent periods as companies adapt their alliance strategy in light of the changing technological environment *(Barley, 1986; Burkhardt & Brass, 1990; Glasmeier, 1991; Lambe & Spekman, 1997; Madhavan, Koka & Prescott, 1998; Soh & Roberts, 2003).* Hence, these periods counterbalance traditional theories of network evolution stating that network endogenous forces lead to durable and self-reproducing network positions *(Baum, Shipilov & Rowley, 2003; Gulati, 1995a, 1995b; Gulati & Garguilo, 1999; Powell et al., 2005)*. Establishing relations with prior alliance partners during technological uncertain periods, results in declining performance *(Goerzen, 2007).* Therefore, the effectiveness of clique-embeddedness is not only dependent on the consequences of technological uncertainty but also on companies' (in) ability to adapt to these changing conditions in their external environment.

In order to gain novel technological knowledge the best strategy is to reach out to new partners *(Christensen & Raynor, 2003; Duysters, 1996).* The likelihood that a clique-member is able to explore and gather new technological knowledge within the clique is limited as compared to the potential of an alliance with a company that is not embedded within the same clique. Hence, technology shifts give clique-members a clear incentive to strategically redesign their network and reconsider their position as clique-member. However, the restructuring of alliance portfolios during or after technological shifts might point to increasing confusion amongst companies as their past alliance strategy did not enable them to adapt swiftly to changing conditions. Hence, companies that established a well balanced set of alliances before technological shifts were better positioned to adapt effectively during these periods. Companies that reached beyond clique-boundaries before these periods already had access to heterogeneous sources of technological knowledge, which is considered a precondition to remain competitive during these periods. Conversely, companies that established relatively more inside clique ties could face serious difficulties during technological uncertainty as these firms face over-embeddedness. Especially during periods of technological uncertainty, firms require a network position that facilitates exploration of new knowledge. Hence, companies that established more clique spanning ties in the past are better positioned during technological shifts and have the ability to adapt to changing conditions in their external environment.

Hypothesis 5: *Clique members that established clique spanning ties in the past are more innovative during periods of technological uncertainty as compared to companies that established mainly inside clique ties in the past.*

4.3 Data and variables.

Data. We constructed a panel dataset that covers the population of ASIC producers over the period 1987-2000. This period captures an important period in the technological development of the ASIC-Industry. Based on the vendor-list included in the ICE ASIC-Outlook industry reports (*McClean, 1987-2000*) we were able to establish a detailed list of all ASIC-producers. The measures of technological knowledge bases draw on patent data from the US Patent and Trademark Office[11]. In particular in industries where companies operate on a global scale, such as the ASIC-industry, U.S. patents are a good proxy for companies' worldwide technological performance and technological assets (*Jaffe & Trajtenberg, 2002*). The data on strategic technology alliances were obtained from the ICE-industry reports; the ASIC-Outlook reports (*McClean, 1977-2000*) and the MERIT-CATI database on strategic technology alliances (*Hagedoorn, 1993*). Financial data of ASIC producers has been gathered from different sources among which the annual ICE reports (*McClean, 1977-2000*) and COMPUSTAT.

Dependent Variables. This paper investigates whether knowledge and technological capabilities of clique members are more homogenous as compared to that of non-clique members. Next, we analyze whether the effectiveness of clique-embeddedness is contingent on the environment in which the firm is competing and on its ability to adapt when external conditions change the competitive landscape. In order to accomplish this goal we make use of two distinct dependent variables.

The first dependent variable looks at the similarities of the knowledge portfolios of clique-members and measures the technological distance between all firms that were 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,*

[11] 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*).

1998; Nooteboom et al., 2007). Within this research we measured technological distance based on the procedure outlined in Jaffe (*1986*). This method calculates technological distance as the uncentered correlation between their respective vectors of technological capital (*cumulative patent applications in technology class k*). Regarding our first hypothesis we are interested in measuring differences in technological distance among companies embedded in the same clique as compared to companies not embedded in the same clique. Therefore, we included all potential dyads that could have been established between all firms reported as clique-members within our observation years. This resulted in an unbalanced panel set of 60.733 pairs of firms for this observation time period. Next, we excluded all firms that did not have at least one ASIC related patent since the configuration of their knowledge bases based on patent indicators could not be determined. Once these firms' pairs were eliminated, 14.166 pairs of firms were left of which the technological distances could be assessed. For our second hypothesis, we included all new dyads in a given year. Within the period 1987-2000 we found 521 new dyads established within the ASIC-Industry. To test hypothesis 1 we measured differences in technological distance amongst inside clique ties and clique spanning ties and we therefore only included these ties in the analysis. This resulted in 416 pairs of firms. Next, we excluded all firms that did not have at least one ASIC related patent –see footnote 1 for a definition of ASIC related patents– since we could not assess a technological profile of these companies. Once these firms' pairs were eliminated we are left with a total of 177 ties were left of which the technological distances amongst the alliance partners could be assessed.

Our second dependent variable is a measure of the technological performance of companies active in the ASIC-industry. We measured technological performance by the number of patents that a company successfully applied[12] for in a particular year, weighted by the number of citations it received afterwards. 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, 2000a; Stuart, 2000; Hagedoorn & Duysters, 2002; Schilling & Phelps, 2007*). We weighted patents by the citations they received afterwards 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 the observation period, we estimated the number of citations patents would receive over their life-span, based on the

[12] 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.

number of citations they received until 2007 using the simulated cumulative distribution lags developed by Hall, Jaffe & Trajtenberg *(2001)*.

Independent Variables. Our first independent variable measures the environmental change within the ASIC-Industry within our observation period. Although environmental change might have various sources, we chose to concentrate on technological change in the empirical analysis. Measures of technological change have been used in prior studies (*Madhavan, Koka & Prescott 1998; Koka & Prescott, 2008; Van de Vrande et al., 2007*). We followed Hannan & Freeman (*1989*) and Delecroix & Swaminathan (*1991*) to measure change as the amplitude of change within the industry of interest. Amplitude of change in patent applications was measured as the relative deviation of the current year's growth from the mean growth rate in patent applications during the preceding 3 years. Before calculating the interaction terms with clique-membership and with firms past alliance behavior we standardized the variables (*Aiken & West, 1991*).

Next to these technological indicators we used social network analysis to measure which firms belong to the same clique. In line with prior research on cliques *(Rowley et al., 2005),* the N-Clan procedure – see section 2.5- implemented in UCINET *(Borgatti, Everett & Freeman, 2002)* was used to detect relevant cliques. The N-Clan procedure allows firms to be embedded in more than one clique and detects cliques based on a predefined maximum distance between all firm in the clique and a predefined minimal size of the clique. By using a maximum distance of 2 we assured that firms in the same clique were connected either by a direct tie or an indirect tie. By using a minimal group size of 5 members we assured that cliques had a significant size to detect variations across cliques in terms of their internal and external linkages.

Next, we categorized the various ties firms formed amongst each other within the ASIC-Industry based on the strategic intentions of these ties. 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).* Regarding the strategic intentions of a firm past alliance behavior, we are interested in the strategic intentions of all new ties that a firm formed within the 5 years prior to the observation year. The strategic intentions of clique-members new tie formation can be classified into "inside clique ties", "outside clique ties with peripheral network members" and "clique spanning ties". If a new tie formed in year *t* bridges two distinct cliques in the alliance network of *t-1* a tie can be considered a clique spanning tie. After categorizing all these ties, the number of clique spanning ties and inside clique ties can be measured by counting the number of those ties that a firm initiated 5 years prior to the observation year.

Control Variables. We included four organizational variables, two clique variables, and four dummy variables to control for unobserved effects. As our first control at the organizational level we included the variable technological capital as an indicator for the total size of a firm's technological knowledge base. This variable was created by summing all ASIC-related patents that a firm successfully applied for 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).* The second firm-level variable relates to the centrality of a firm in the overall alliance network. Being located in the center of an alliance network has been recognized as an important and distinctive form of social capital of innovating firms *(Gulati, 1995a; 1999).* To measure centrality we used the measure of eigenvector centrality *(Bonacich, 1972).* Eigenvector centrality is a measure of the importance of a firm in the alliance network. It assigns relative scores to all firms in the network based on the principal that connections to high-central firms are more important than connections to firms that are less central. Hence, this measure incorporates the centrality of all network participants and calculates a firms' centrality based on the centrality of the firms it has alliances with. Hence, having an alliance with a central company provides a higher eigenvector centrality than an alliance with a peripheral firm.

The third firm-level variable relates to the size of the firm. Large firms have a broader and more diversified established network of alliances *(Hagedoorn & Duijsters, 2002)* and place themselves as dominant firms not only within the 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 have a higher potential to increase their technological performance over time. We calculated this variable based on the natural logarithm of a firm's annual sales. The fourth firm-level control 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. We calculated this variable based on the R&D to sales ratio of each firm.

Furthermore, we include four types of dummy variables to control for different types of contingencies. A first dummy variable was included to control for a potential bias as some large companies produce ASIC's only for their internal needs. These captive producers are a small minority of ASIC-producing companies but 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*). Second, industry dummy variables were included to indicate the industry to which an ASIC-producer belongs. Firms can be involved in the production of only one segment or 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 third dummy variable indicates in which economic region the company is headquartered (*Asia, North America or Europe*), with the default being 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 6 provides a detailed overview of all measures that have been used within the empirical analysis.

4.4 Results.
In Table 7, descriptive statistics and the correlation matrix for the different variables are presented. The data presented in this table applies to both clique-members and non-clique-members. Table 9 presents descriptive statistics and the correlation matrix for the subsample which includes only clique-members. Hypotheses 1 predicts that technological distance between clique-members are on average smaller than the technological distance between companies that belong to different cliques. Similarly, hypothesis 2 predicts that the technological distance between two partners that established clique spanning ties will be larger than the technological distance between partners that established inside clique ties. In order to test for the significance of these differences in technological distance, we used a t-test. Table 8 shows the results of the t-tests related to hypotheses 1 and 2.

In hypotheses 1 and 2 we investigate differences in technological distance related to firms' position in the clique. Hypothesis 1 states that the technological distance between members of different cliques is larger as compared to the technological distance between companies embedded within the same clique. The technological distance measure takes a value between 0 and 1, according to the extent that their technological knowledge overlaps. Our empirical results show that the technological distance between members of the same clique *(mean technological distance: 0.57; s.d. 0.25)* is significantly smaller than the technological distance of companies embedded in different clique *(mean technological distance: 0.63; s.d. 0.34).* These results are in support of hypothesis 1 and indicate that the knowledge bases of companies embedded within the same cliques are more similar than knowledge bases of companies embedded in different cliques. Hypothesis 2 predicted that the technological distance of clique spanning ties is significantly larger than the technological distance of an inside tie. Our empirical results indicate that the technological distance of an inside clique tie *(mean technological distance 0.53; s.d. 0.28)* is significantly smaller than the technological distance of a clique spanning tie *(mean technological distance 0.62; s.d. 0.30).* These results support hypothesis 2 and show that the formation of a clique spanning tie connects a firms to knowledge that is more novel to this firm than the formation of inside clique ties. Hence, firms have a clear incentive to look beyond local search in the alliance network when looking for knowledge with a high novelty value in relation to a firms' own knowledge base.

The dependent variable in hypotheses 3, 4 and 5, weighted patent counts, is a count variable. Because our data shows 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, indicating that random effects negative binomial model is not a consistent estimator. As a result, a fixed effects model was used for the models in the next tables. Tables 10 and 11 present the results of the fixed effects negative binomial regressions. Because these hypotheses used different samples, we estimated two different models. The results regarding hypotheses 3 and 5 are reported in Table 11, the results with regard to hypotheses 4 are reported in Table 10. Within both tables we present baseline models (*model 1 and 5*), controlling for companies' technological distance, technological capital, size, R&D intensity whether or not they are captive producers of ASICs, and region and year specific effects.

Models 6 and 7 presented in Table 11 reflect 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. In order to calculate the effects of both variables on innovative performance we computed multipliers to calculate how large these effects are in real terms. The multipliers are calculated as increases in each variable of two standard deviations[13] *(Rowley et al., 2005).* The results indicate that the effect of clique spanning ties on innovative performance is 1,90 *(coefficient 0.26; standard deviation 1.23)* and of inside clique ties on innovative performance is 1,68 *(coefficient 0.13; standard deviation 2.01).* These results support hypothesis 3 and confirm that the formation of clique spanning ties contributes to the innovative performance of clique members.

[13] Multiplier + 2 s.d. = exp (b* 2 s.d.)

Table 6: Definitions of dependent and independent variables.

Variable name	Variable description
Innovative performance	Count variable indicating the number of successful patent applications, weighted by the number of citations they receive.
Technological uncertainty	Amplitude of change as relative growth of number of patents between year $_{(t1)}$ over the mean of the preceding 3 years $_{(t2-4)}$
Clique membership	Dichotomized variable (0/1) indicating if a firm is a clique member in alliance network $_{(t1-5)}$
Past inside clique ties	Prior ties that a firm formed inside its own clique $_{(t1-5)}$
Past clique spanning ties	Prior ties that a firm formed that brokered two different cliques $_{(t1-5)}$
Technological Distance	Technological distance between the focal firm and its partners based on their patent portfolios $_{(t1-cum)}$
Technological Capital	Count variable indicating the number of successful patent applications in $_{(t1-5)}$
Firm Size	Total overall sales of the focal firm/1000 $_{(t1)}$
Firm R&D	Firm total R&D expenditures / Firm overall sales $_{(t1)}$
Captive producer	Dummy variable denoting that the firm is not selling products on the ASIC-market
SC-Producer	Dummy variable denoting that the firm is producing only Standard Cells
PLD Producer	Dummy variable denoting that the firm is producing only PLDs
GA-SC Producer	Dummy variable denoting that the firm is producing only Gate Arrays and Standard Cells
GA-PLD Producer	Dummy variable denoting that the firm is producing only Gate Arrays and PLDs
SC-PLD Producer	Dummy variable denoting that the firm is producing only Standard Cells and PLDs
GA-SC-PLD Producer	Dummy variable denoting that the firm is producing Gate Arrays and Standard Cells and PLDs
European Firm	Dummy variable denoting that the firm is headquartered in Europe
Asian Firm	Dummy variable denoting that the firm is headquartered in Asia
Trend	Variable denoting the year of observation

Table 7: Descriptive statistics and correlation matrix.

	Variable	1	2	3	4	5	6	7	8	9	10
All firms (848 obs.)											
1	Inn. perf.	1.00									
2	Techn. unc.	-0.04	1.00								
3	Clique-memb	0.16	-0.03	1.00							
4	Tecchn. Dist.	-0.11	-0.01	-0.06	1.00						
5	Techn. Cap.	0.76	-0.05	0.22	-0.14	1.00					
6	Firm Size	-0.05	-0.01	0.20	-0.05	0.06	1.00				
7	Firm R&D	0.07	0.03	0.01	-0.10	0.02	-0.35	1.00			
8	Captive	-0.11	0.02	-0.03	0.02	-0.13	0.19	-0.14	1.00		
9	European	-0.09	0.01	0.10	0.00	-0.11	0.08	-0.03	0.09	1.00	
10	Asian	-0.12	-0.03	0.01	0.09	-0.03	0.19	-0.39	-0.16	-0.25	1.00
	Mean	97.85	0.36	0.66	0.52	10.93	1.42	0.11	0.17	0.14	0.28
	S.D.	312	0.30	0.48	0.22	24.06	2.21	0.08	0.37	0.34	0.45
	Minimum	0.00	0.04	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00
	Maximum	3792	1.00	1.00	1.00	307	16.41	0.87	1.00	1.00	1.00

Table 8: Results for technological distance.

Variable	Mean	SD	Obs
Position in network			
Same clique	0.57	0.25	3.230
Different cliques	0.63	0.34	11.936
t-test: p=<.05**			

Variable	Mean	SD	Obs
New tie Formation			
Inside clique tie	0.53	0.28	63
Clique spanning tie	0.62	0.30	61
t-test: p=<.001***			

Table 9: Descriptive statistics and correlation matrix.

	Variable	1	2	3	4	5	6	7	8	9	10	11
Clique-members (517 obs.)												
1	Innovative performance	1.00										
2	Technological uncertainty	-0.04	1.00									
3	Past inside clique ties	-0.05	0.02	1.00								
4	Past clique spanning ties	0.08	-0.01	0.40	1.00							
5	Technological Distance	-0.11	0.02	-0.11	-0.09	1.00						
6	Technological Capital	0.73	-0.05	0.02	0.21	-0.14	1.00					
7	Firm Size	-0.11	-0.01	0.14	0.16	-0.00	0.00	1.00				
8	Firm R&D	0.07	-0.06	-0.08	-0.07	-0.12	0.01	-0.43	1.00			
9	Captive	-0.13	0.03	-0.10	-0.12	0.06	-0.15	0.19	-0.17	1.00		
10	European	-0.14	0.00	0.41	0.02	0.06	-0.17	0.04	-0.03	0.15	1.00	
11	Asian	-0.14	-0.02	-0.16	-0.10	0.12	-0.05	0.23	-0.42	-0.13	-0.28	1.00
	Mean	144.06	0.35	1.47	1.21	0.49	15.62	1.80	0.11	0.16	0.17	0.27
	Standard Deviation	373.54	0.29	2.01	1.23	0.24	27.21	2.43	0.07	0.37	0.38	0.45
	Minimum	0.00	0.04	0.00	0.03	0.00	0.00	0.00	0.01	0.00	0.00	0.00
	Maximum	3791.54	1.00	9.00	8.00	1.00	307.00	16.41	0.67	1.00	1.00	1.00

Table 10: Fixed effects panel estimation results for Innovative performance (All Firms).

	(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)***
Cl.-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)***
Firm R&D	-0.38 (0.79)	-0.31 (0.81)	-0.34 (0.87)	-0.41 (0.88)
Captive	-0.14 (0.20)	-0.15 (0.20)	-0.15 (0.20)	-0.15 (0.20)
GA	-1.50 (0.31)***	-1.49 (0.31)***	-1.32 (0.31)***	-1.32 (0.31)***
SC	-1.68 (0.26)***	-1.70 (0.26)***	-1.61 (0.26)***	-1.62 (0.26)***
GA-SC	-0.82 (0.22)***	-0.83 (0.22)***	-0.88 (0.22)***	-0.88 (0.22)***
SC-PLD	0.20 (0.46)	0.18 (0.46)	0.01 (0.46)	0.00 (0.46)
GA-PLD	0.62 (0.28)**	0.63 (0.27)**	0.55 (0.27)**	0.55 (0.27)**
GA-SC-PLD	-0.42 (0.23)*	-0.42 (0.23)*	-0.47 (0.23)**	-0.48 (0.23)**
European Firm	-0.32 (0.21)	-0.32 (0.21)	-0.37 (0.21)*	-0.37 (0.21)*
Asian Firm	0.17 (0.17)	0.16 (0.17)	0.26 (0.17)	0.25 (0.17)
Constant and year	Included	Included	Included	Included
Obs. (firms)	848 (71)	848 (71)	848 (71)	848 (71)
Log Likelihood	2587,67	2586,49	2571,54	2571,42

Table shows results of fixed effects negative binomial model
Note 1: *** p < 0.01; ** p < 0.05; * p < 0.10
Note 2: Standard Deviations in Parentheses

Table 11: Fixed effects panel estimation results for Innovative performance (Clique-Mem).

	(5)	(6)	(7)	(8)	(9)	(10)
Inside Ties		0.13 (0.04)***			0.13 (0.04)***	
Clique Sp. Ties			0.26 (0.04)***			0.28 (0.04)***
Turbulence				-0.30 (0.15)*	-0.43 (0.20)**	-0.56 (0.22)***
Inside tie*Turb.					0.04 (0.03)	
Clique Sp.Tie*Turb.						0.07 (0.03)**
Techn. Distance	-1.01 (0.26)***	-1.03 (0.26)***	-1.02 (0.26)***	-0.97 (0.26)***	-0.98 (0.26)***	-0.99 (0.26)***
Techn. Capital	0.01 (0.00)***	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)**	0.06 (0.03)*	0.05 (0.03)
Firm R&D	-0.77 (1.25)	-0.82 (1.26)	-0.72 (1.23)	-0.91 (1.25)	-0.84 (1.26)	-0.85 (1.24)
Captive	-0.08 (0.24)	-0.04 (0.24)	0.17 (0.23)	-0.09 (0.24)	-0.06 (0.24)	0.13 (0.23)
GA	-1.23 (0.48)**	-1.19 (0.48)**	-1.32 (0.48)***	-1.23 (0.48)**	-1.17 (0.48)**	-1.29 (0.48)***
SC	-1.40 (0.31)***	-1.43 (0.31)***	-1.67 (0.31)***	-1.43 (0.31)***	-1.44 (0.31)***	-1.67 (0.31)***
GA-SC	-0.79 (0.24)***	-0.87 (0.24)***	-1.00 (0.24)***	-0.83 (0.24)***	-0.90 (0.24)***	-1.04 (0.24)***
SC-PLD	-0.10 (0.46)	-0.64 (0.49)	-0.18 (0.44)	-0.13 (0.46)	-0.70 (0.49)	-0.27 (0.44)
GA-PLD	0.46 (0.29)	0.48 (0.28)*	0.52 (0.28)*	0.45 (0.29)	0.46 (0.28)*	0.52 (0.27)*
GA-SC-PLD	-0.30 (0.25)	-0.58 (0.26)**	-0.49 (0.25)*	-0.33 (0.25)	-0.57 (0.26)**	-0.55 (0.25)**
European Firm	-0.64 (0.23)***	-0.92 (0.24)***	-0.65 (0.23)***	-0.65 (0.23)***	-0.91 (0.24)***	-0.67 (0.23)***
Asian Firm	0.21 (0.21)	0.37 (0.21)*	0.40 (0.21)*	0.18 (0.21)	0.33 (0.21)	0.34 (0.21)
Constant & year	Included	Included	Included	Included	Included	Included
Obs. (firms)	517 (51)	517 (51)	517 (51)	517 (51)	517 (51)	517 (51)
Log Likelihood	2022,83	2016,22	2003,06	2021,16	2013,73	1999,26

Table shows results of fixed effects negative binomial model
Note 1: *** p < 0.01; ** p < 0.05; * p < 0.10
Note 2: Standard Deviations in Parentheses

Models 2 to 4 in Table 10 reflect the results of the test whether the effect of clique membership on innovative performance is smaller during periods of technological uncertainty compared with periods of technological stability. Again, we entered the effects in a stepwise way showing the results of technological uncertainty (*model 2*), technological uncertainty and clique membership (*model 3*) and the interaction effect (*model 4*). The results in these models reject hypothesis 4 and indicate that clique-membership is beneficial even during technological turbulent periods. Hence, within the ASIC-industry, companies embedded within cliques reap the benefits of this strategy during periods of technological stability as well as during periods of technological uncertainty.

Clique membership might be beneficial for clique members in general. However, it is interesting to restrict our attention to clique members only and to look at individual differences between clique members, checking whether their relational and technological capital helps in overcoming turbulent periods. Models 8 to 10 in Table 11 report the results of the tests of hypothesis 5 which looks at the effect of past clique spanning ties and inside clique ties on innovative performance during periods of technological uncertainty. Contrary to the overall population including also ASIC-producers that are not a member of the clique (*model 2, Table 10*), technological uncertainty has a slightly negative effect on the innovative performance of clique-members (*model 8, Table 11*). This result is interesting in itself as it indicates that the innovative performance of non-clique members is responsible for finding a non-significant estimator of technological uncertainty for the overall population. In model 9 we add the interaction effect of inside clique ties during periods of technological uncertainty. This model indicates that only the main effects of past inside clique ties (*positive*) and technological uncertainty (*negative*) influence the innovative performance of companies in the ASIC-industry. Hence, during technological turbulent periods having established past inside clique ties does not protect a clique-member from the negative effects of these periods. As model 10 demonstrates we find support for hypothesis 5, indicating that the establishment of clique spanning ties in fact does provide companies with sufficient access to a variety of contacts to be better prepared to technological uncertainty. Clique-members that established past clique spanning ties have more access to non-redundant knowledge which serves as a protecting mechanism during these unpredictable periods.

4.5 Discussion and Conclusions.

Within alliance networks durable and self-reproducing network positions become observable over time as firm behavior increases repeated ties among the already embedded firms *(Baum, Shipilov & Rowley, 2003; Gulati & Garguilo, 1999; Powell et al., 2005).* This so-called *structural differentiation* segments the overall network into semidetached cliques of repeatedly cooperating sets of firms *(Baum, Shipilov & Rowley , 2003; Rosenkopf & Padula, 2008).* 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)*. While clique-embeddedness is generally considered to enhance performance *(Lazzarini, 2007; Rowley et al., 2004),* there are also reasons to expect that under some circumstances clique-embeddedness is less beneficial or might even become a liability. One of these exceptions which could affect the effectiveness of clique-embeddedness is when technological change makes existing knowledge bases obsolete. During these shifts clique-members are not necessarily in a beneficial position as radical *(Leifer et al., 2000)* and potentially disruptive new technologies *(Christensen, 1997; Christensen & Raynor, 2003)* originate in many cases in peripheral companies that challenge market leaders. In order to gain a deeper insight into the effect of technological uncertainty on the effectiveness of clique-embeddedness we investigated some of the underlying mechanisms of clique-embeddedness which become relevant during these periods of uncertainty: the opportunity to access technological knowledge within the clique and the ability to adapt during these periods.

The similarity of technological knowledge within the clique can be seen as the result of the process of interaction as companies internalize their partner's knowledge, which cause them to become more alike over time *(Mowery, Oxley & Silverman, 1996; Brass, Butterfield & Skaggs, 1998; Gilsing et al., 2008; Wuyts et al., 2005).* This could become a serious threat as the decreasing heterogeneity of knowledge and technologies inside the clique is not equipped for the exploration of new knowledge and technologies *(Burt, 2000; Rowley et al., 2000).*Our findings support the notion that knowledge and technological profiles are more similar for companies embedded within the same clique than companies not embedded in the same clique. Therefore, establishing clique spanning ties connect companies to knowledge and technologies that are more novel to its current knowledge than the formation of an inside clique tie. Together these findings indicate that companies have a clear incentive to look beyond their clique-boundaries when looking for technological knowledge that is more novel to its current knowledge base. Further analysis indicated that both the formation of inside clique ties and clique spanning ties have positive effects innovative performance. However the formation of clique spanning ties enhances innovative performance more than the formation of additional inside clique ties. The formation of clique spanning ties allows learning and absorbing technological knowledge that is more novel to clique-members' current technological knowledge which contributes to their innovative performance.

We also expected that clique-membership might become a liability during periods of turbulence or uncertainty. Turbulent environments require a network position that facilitates exploration of new 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 clique-membership is less beneficial during periods of technological change. Next, we also looked at companies' (in) ability to adapt to the changing conditions in their external environment since especially during technological turbulent periods, companies are constantly challenged to improve their learning and strengthen or renew their technological capabilities *(Cohen & Levinthal, 1989; March, 1991).* We found that the formation of past inside clique ties does not affect companies' innovative performance during technological turbulent periods. However, having formed more clique spanning ties in the past does positively influence companies' innovative performance during technological turbulent periods.

The current study has several limitations and directions for future research. First, it is limited to a single sector and therefore we should be cautious extrapolating these results towards other industries. Furthermore, within this study we did not incorporate variables that controlled for heterogeneity across cliques such as the age, size, density or performance of the clique. These aspects might affect the innovative performance of clique-members during periods of technological uncertainty as the availability of technological knowledge inside the clique as a whole will influence a firm's ability to get access to non-redundant knowledge. Furthermore, this study was limited to a single technique -i.e. N-Clan- that was able to detect overlapping cliques. While the decision to use this technique was based on theoretical motivations, it might be interesting from a methodological point of view to test whether other cluster techniques provide different results to our analysis. Since research on cliques is gaining momentum within IOR literature, a more systematic review and/or simulation upon the methodological characteristics underlying these various techniques would be a valuable contribution to current literature. The clique is however gaining momentum in the managerial literature with a potential to link multiple levels of analysis in the network literature *(Baum, Shipilov & Rowley, 2003; Lazzarini, 2007; Padula, 2008; Rosenkopf & Padula, 2008; Rowley et al., 2004; 2005).* Our results indicate that clique-membership does enhance a firm's innovative performance, but that not all that glitters is gold for all members of the clique. Knowledge available within the boundaries of the clique is significantly more homogenous than knowledge available outside the boundaries of the clique. Not all clique-members can equally profit from their clique membership and these differences are more pronounced during technological turbulent periods. Clique-members that established more alliances that link them to knowledge of firms in other cliques are more innovative in technological uncertain periods than clique-members lacking these types of alliances.

Chapter 5: Going beyond local search

Abstract
Alliance cliques have been largely neglected in technological alliances studies. In this study we show that cliques offer an interesting angle to analyze why certain firms are better in going beyond local search than others. Clique spanning ties can be expected to have strategic advantages for firms maneuvering themselves in a position as broker between two dense regions in the alliance network. We examine the effects of technological and network variables and find strong evidence that both factors play a considerable role in explaining the probability that firms go beyond local search in alliance networks.

Keywords: alliance networks; clique membership; technology profiles; innovative performance

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5.1 Introduction.

A major question that has preoccupied management scholars is *why* firms establish alliances and alliance networks *(see Gulati 1998 for a review).* Recently, an interest has arisen in *how* alliances or alliance networks originate and evolve over time, with network actions and positions as the variables of interest. Under pressure of both 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).* These changes can be triggered by changes external to the alliance network such as economical, institutional or technological changes *(Ahuja, 2000b; Barley, 1986; Burkhardt & Brass, 1990; Katila & Mang, 2003; Madhavan, Koka & Precott.1998; Soh & Roberts; 2003).* In addition, several studies have identified characteristics internal to the existing alliance network as drivers of alliance network change such as prior alliances between two alliance partners, network centrality, local network density, and structural holes *(Baum, Shipilov & Rowley, 2003; Gulati, 1995a; 1995b; Gulati & Garguilo, 1999; Powell, White, Koput & Owen-Smith; 2005).*

The existing literature still seems to take on a rather deterministic approach to network structure and positioning in which firms are primarily influenced by forces external to the alliance network. Consequently, most of this work neglects the effects of the existing alliance network structure on new tie formation processes. Gulati and Garguilo (*1999*) were among the first to provide empirical evidence indicating that a firm's prior position in the alliance network influences its opportunities to form new ties. Their research findings indicate that companies with prior cooperation, common third parties, and a central network location are more likely to establish new ties amongst each other *(Gulati & Garguilo, 1999).* In line with those results, recent research focuses on the influence of the existing alliance network on new tie formation processes *(Ahuja, 2000b; Baum et al., 2003; Garguilo & Benassi, 2003; Powell et al., 2005; Stuart, 1998; Tsai, 2000).*

Over time, forces internal to the existing alliance network lead to durable and self-reproducing network positions, as firm behavior increases repeated ties among the already embedded firms *(Baum, Shipilov & Rowley, 2003; Gulati & Garguilo, 1999; Powell et al., 2005).* This so-called *structural differentiation* segments the overall network into semidetached cliques of repeatedly cooperating sets of firms *(Baum, Shipilov & Rowley, 2003; Rosenkopf & Padula, 2008).* While most research findings on forces internal to the existing alliance network indicate that the evolution of network structures lead to a definite structural pattern over time, it is very likely that these effects are not the same in every industry setting. According to Gulati & Garguilo (*1999; p.1478*) "*a different force* might be in place in new, extremely dynamic and innovation driven industries, where all players could benefit from alliances with almost any other player". As competition puts increasing demands on firms to keep their technological knowledge bases competitive, firms must overcome their tendency to be locally biased and path dependent in their search processes to form new ties *(Gulati, 1995a; Stuart & Podolny, 2000; Walker, Kogut & Shan, 1997).* Under influence of extreme competition in these innovation driven industries, which can be considered as an external driver of alliance network change, firms counterbalance the process of structural differentiation by going beyond local search in the alliance network.

Within the domain of technology alliance networks, the effects of technology as an external driver of alliance networks change has been explored at different levels of analysis. The majority of these studies focused on the firm, the dyad, and the network level of analysis *(Ahuja, 2000b; Katila & Mang, 2003; Madhavan et al., 1998; Stuart, 1998).* Surprisingly, research within this field has neglected the effects of technology as an external driver of alliance network change at the clique level of analysis. Cliques are subsets of actors among whom there are relatively strong, direct, intense, frequent and/or positive ties *(Wasserman & Faust, 1994).* Clique membership positively affects performance of its members in industries such as health care *(Provan & Sebastian, 1998),* micro-processors *(Gomes-Casseres, 1996),* airline operations *(Lazzarini, 2007)* and investment banking *(Rowley et al., 2004).*

While insights in the rationale and mechanisms underlying new tie formation are increasing *(e.g. Ahuja 2000b; Gulati, 1995a, 1995b; Gulati & Garguilo, 1999; Hagedoorn, 1993, 1996; Nohria & Garcia-Pont, 1991; Silverman & Baum, 2002; Stuart, 1998, 2000),* there is only a handful of studies investigating the dynamic differentiation of ties in terms of their network structural properties relating to the clique. One notable exception is the study of Baum et al. (*2003*) where the joint effects of events external and forces internal to the existing alliance network on the formation of new *clique spanning ties –ties linking firms in different cliques-* are tested within the environment of Canadian investment banks. Another exception is the recent study by Rosenkopf & Padula (*2008*) who empirically tested the micro-dynamics behind partner selection within the technological environment of the mobile communications industry, i.e. the formation of *clique spanning ties* and the *entry of new firms to the main component*.

By forming a clique spanning tie, firms maneuver themselves in a broker position by establishing a new tie to other central parts of the overall network. According to Baum et al. (*2003, p.704*) "firms in a broker position create information asymmetry between themselves and other firms, in such a way as to increase the dependence of other firms on them and to strengthen in this way their power in the network". Clique spanning ties can thus be expected to have positive rents for firms maneuvering themselves in a position as broker between two cliques. While most studies have shown motives why firms tend to be locally biased and path-dependent in their search strategies *(Gulati, 1995a; Stuart & Podolny, 2000; Walker et al., 1997),* relatively less is known about situations in which firms may opt for forming a clique spanning tie. The current study intends to fill this uncharted field by exploring the underlying dynamics of new tie formation that span the boundaries of dense cliques in an alliance network. To date, Baum et al. (*2003*), and Rosenkopf and Padula (*2008*) have provided a baseline model to jointly explore the effects of factors external and internal to the existing alliance network on the formation of clique spanning ties. However, to our knowledge no prior research focused on the role of technological knowledge bases as a driver of the establishment of clique spanning ties within extremely dynamic and innovation driven industries. Therefore, in this paper we examine how a firm's technological knowledge base and its position in the existing alliance network influence its potential to form these ties within these industries. The results in the empirical section confirm that a firms' technological knowledge base as well as its position in the existing alliance network play an important role in explaining the probability new ties that cross clique boundaries are established.

This paper is organized as follows. First, a more detailed background regarding the hypotheses on how technological and network variables affect the formation of clique spanning ties is provided. Second, a detailed description of the data, variables and methods we use to test our hypotheses is given. Third, an overview is presented of the most important results based on a longitudinal dataset covering technological activities, alliance strategies, and financial data with regard to the population of producers of ASICs (*application-specific integrated circuits*) in the period 1987-2000. In the last section conclusions are drawn and the managerial implications of the main research findings are discussed.

5.2 Theory and Hypotheses.

Although all different forms of ties are important in their own right, the current paper focuses on clique spanning ties. These ties can lead to strategic advantages for firms who intend to maneuver themselves in a position as broker between two cliques *(Baum, Shipilov & Rowley, 2003, Rosenkopf & Padula, 2008).* We hypothesize that under particular circumstances firms have incentives to look for new partners beyond the current set of clique members. In other cases, these firms can be attractive alliance partners, inducing firms in other cliques to establish clique spanning ties. We argue that the probability of a firm to establish a clique spanning tie is influenced by the characteristics of its technological knowledge base. Furthermore we argue that firm size plays a moderating role in determining the impact of the firm's technological knowledge base on the likelihood of the formation of a new clique spanning tie. Finally, we hypothesize that experience with clique spanning ties and embeddedness within the clique influences the establishment of new clique spanning ties.

Technology knowledge base characteristics. External acquisition of technology is becoming a major source of innovation *(Ahuja & Katila, 2001; Chesbrough, 2003; Grandstrand, Oskarsson & Sjoberg 1992; Hagedoorn & Schakenraad, 1994; Keil, 2002; Powell, 1998; Teece 1992).* Technology based alliance networks increasingly play a critical role in this acquisition process *(Ahuja, 2000a; Katila & Mang, 2003; Rosenkopf & Almeida, 2003; Schilling & Phelps, 2007; Stuart, 1998).* At the same time, the evolution of (*technology based*) alliance networks has only recently received some attention, although most scholars agree that a longitudinal view on alliance networks is required to analyze a series of interesting research questions *(Nohria, 1992).*

As argued before, under stable conditions firms tend to be path-dependent and locally biased in their partnering strategy, enforcing firms that work in cliques into a sort of strategic gridlock *(Gomes-Casseres, 1996).* Prior research indicates that a firm's attractiveness to potential partners and hence its opportunities to collaborate are likely to vary positively with its technological knowledge base *(Ahuja, 2000b; Dutta & Weiss, 1997; Katila & Mang, 2003; Rosenkopf & Almeida, 2003; Stuart, 1998; Zhang, Baden-Fuller & Mangematin, 2007).* Therefore, firms with a valuable technological knowledge base attract attention from other firms who are interested to get access to these resources. While these findings all indicate that a positive relationship exists between the size of a firm's knowledge base and the number of linkages formed by the firm, knowledge about the relationship between a firm's knowledge base and its inducements and opportunities in the formation of clique spanning ties is negligible.

Cutting edge technology that does not build on prior knowledge available in the industry has the potential to make existing routines, knowledge and competences obsolete. Over time these technologies lead to shifts in centrality, centralization and relationships between cliques *(Madhavan, Koka & Prescott, 1998).* According to these authors (*p. 455*), the company that benefits during these shifts, "depends on a firm's ability to attract desirable partners, its motivation to improve its position, and whether it has an opportunity to do so." Especially within extremely dynamic and innovation driven industries, a firm's decisions to partner beyond its clique members will be based on the possibility to link to firms possessing radical new and pioneering technologies since these technologies will be the basis for the future. Firms with many pioneering technologies in their technological knowledge base can be considered as firms that explore new technological fields which will become the bases for future competition *(Ahuja & Lampert, 2001).* Hence, within these extremely dynamic and innovation driven industries, firms possessing pioneering technologies have the opportunity to attract attention from outside their clique. Therefore, other things being equal, clique members with a valuable technological knowledge base are more attractive partners compared to other clique members. As a result, we argue that the possession of pioneering technologies has a positive effect on the number of clique spanning ties.

Hypothesis 1: Pioneering technologies in a firm's technological knowledge base have a positive effect on the number of its clique spanning ties.

Firms with unique technological resources are likely to be attractive to other firms that expect to benefit from getting access to these valuable resources by means of the formation of an alliance. As a result, these firms have more opportunities to establish new ties than firms with a less attractive technological knowledge base. However, significant variation could be caused by a firm's ability to utilize the partnering potentials triggered by the attractiveness of its technological knowledge base. Resources play a critical role in the formation of alliances since firms with more resources have more capacity to cooperate *(Walker, Kogut & Shan, 1997).* Given that resources play a critical role in the formation and maintenance of alliances, larger firms have more possibilities to establish new ties *(Gulati & Garguilo, 1999),* and they also have more opportunities to establish clique spanning ties *(Baum, Shipilov & Rowley, 2003).* Large firms have more employees and have a broader range of contacts in the business and engineering community, which provide them with more visibility and a broader opportunity set to form new alliances beyond the scope of their clique. Mainly due to these forces, large firms that recently developed a valuable technology, with knowledge that is new to the industry, will have a larger appeal as an alliance partner since these larger companies have greater market coverage *(Stuart, 1998).* Reputation effects might also be in place, as teaming up with a larger strategic partner is considered more valuable than an alliance with its smaller counterpart *(Stuart, 2000).* Pioneering technologies -by definition- do not build on prior knowledge and are in this since very risky to invest in. Partnering with large firms is a safer bet than teaming up with a small firm with fewer opportunities for successfully translating pioneering technologies into profitable innovations or new products. Furthermore, due to liabilities of smallness and group pressures these smaller firms could be less inclined to form ties beyond the scope of the clique, even if these smaller firms have formed a technology that is valuable and new to the industry.

Therefore we expect considerable variation in clique members' ability to exploit the opportunity given by a firm's pioneering nature of its technological knowledge base. While hypothesis one argues that pioneering technologies in a firm's technological knowledge base will have a positive effect on the number of clique spanning ties, we also expect that this effect is strengthened by the size of the firm. Larger firms have more resources, a larger appeal, broader visibility and face less group pressures and therefore, have more possibilities to form ties beyond the boundaries of their clique. Consequently, we expect to find that the effect of pioneering technologies on the formation of clique spanning ties is strengthened by the size of firm.

> *Hypothesis 2:* *Pioneering technologies in a firm's technological knowledge base have a positive effect on the number of its clique spanning ties, but this effect is strengthened by the size of the firm.*

Alliance network characteristics. While the first two hypotheses focused on technology as an external factor determining the likelihood of clique spanning ties, other factors that are internal to the existing network may also determine the formation of these ties. Inspired by the seminal work of Granovetter (*1973*), Coleman (*1988*) and Burt (*1992*) many authors have dealt with the question which specific structural network position enables firms to achieve the highest level of performance. Social capital refers to the potential benefits of alliance networks as well as the resources embedded in that network that may be accessed and mobilized for purposive actions *(Burt, 1992).* These relations are path-dependent as prior ties determine the formation of future linkages *(Gulati, 1995b, 1999; Levinthal & Finchmann, 1988, Tsai, 2000; Walker, Kogut & Shan, 1997).* Past research already indicated that factors internal to the existing alliance network such as central network positions, common third parties and prior cooperation can be seen as an indicator of new tie formation *(Ahuja, 2000b; Baum, Shipilov & Rowley, 2003; Gulati & Garguilo, 1999; Powell et al., 2005; Stuart, 1998; Tsai, 2000).* Below we argue that a firm's prior experience with clique spanning ties (*H3*) and its embeddedness in the clique (*H4*) are characteristics internal to the existing alliance network that will also influence its potential to establish clique spanning ties.

Experience. Research findings indicate that firms build up organizational routines and capabilities in alliance management, which can be a source of competitive advantage *(Dyer & Singh, 1998, Rothaermel & Deeds 2006).* An important foundation for these inter-organizational routines and capabilities stems from the fact that firms learn from their prior partnering experiences. These learning processes can be observed in many different alliance formation settings. For example, firms with more alliances in the past establish relatively more alliances in a given year *(Gulati, 1999).* Furthermore, the probability of a new alliance between two organizations increases with the number of prior direct alliances between those organizations, since these prior experiences support firms in learning about each other competences and reliability *(Gulati & Garguilo, 1999).* Other sources show that firms that establish a more diversified set of alliances, (*e.g. equity, non-equity alliances*) develop more experience or capabilities than those with a more narrow set of alliance types *(Heimeriks, Duysters & Vanhaverbeke, 2007; Larsson et al., 1998; Zollo, Reuer & Singh, 2002).* While all these sources indicate that firms acquire inter-organizational routines and capabilities by learning from their past alliance experience, it does not necessarily imply that firms learn from their past experience with clique spanning ties.

After forming a clique spanning tie, firms might have become more aware of the benefits associated with this alliance strategy *(Baum, Shipilov & Rowley, 2003).* Firms learn about the benefits they experience by controlling streams of information and increasing the dependence of firms on them. Firms forming relatively more clique spanning ties build up valuable experiences and capabilities by establishing and maintaining alliances outside their familiar group of partners. The underlying learning mechanism can be linked to issues of trust and uncertainty since these ties that cross clique boundaries cannot rely on existing arrangements already settled within the clique. Hence, firms that start to appreciate the benefits associated with the formation of clique spanning ties acquire valuable experiences and capabilities in order to cope with the lack of trust and uncertainty associated with this type of alliance strategy.

However, the benefits of establishing bridging ties are not long-lived since these ties, relative to other kinds of relationships, show faster rates of decay over time *(Burt, 2002).* Therefore, firms intending to profit from the benefits associated with the formation of clique spanning ties also have a motivation to build up experiences on maintaining active clique spanning ties or by forming additional clique spanning ties. Experience with clique spanning ties delays the decay of these ties over time and becomes a valuable competitive advantage. Hence, these arguments indicate that the likelihood of the establishment of clique spanning ties is influenced by a firm's experience with clique spanning ties. Therefore, we expect a positive relation between prior alliance behaviors and the formation of clique spanning ties is expected.

> *Hypothesis 3:* *Experience with clique spanning ties in the past has a positive effect on the number of future clique spanning ties.*

Clique embeddedness. In order to describe the full dynamics behind the formation of clique spanning ties, the effect of a firm's position within the clique has also be taken into account. Firms that are clique members are embedded within a structure which influences a firm in its consequent network actions. Clique embeddedness indicates that actors who are integrated in these cliques face different sets of resources and constraints than those who are not embedded in the same clique *(Moody & White, 2003).* Within each clique firm-variation is observable because each firm has its own unique position within the clique, ranging from preponderance of ties inside their own clique to a position in which a firm maintains a network with a higher outward clique orientation. From the perspective of the clique this implies that it contains firms that are central and other firms that are peripheral within the clique.

Clique-membership has been shown to positively influence firm performance *(Rowley et al., 2004; Lazzarini, 2007).* The danger of clique embeddedness however, is the tendency to produce more familiar technological know-how with a low novelty value *(Gilsing et al., 2008; Wuyts, 2005).* New partners belonging to other cliques (*or peripheral firms*) are more likely to bring new, unfamiliar technological knowledge into the focal firm. Over time, embedded clique structures could diminish the positive returns associated with this partnering strategy. As a result, this so-called over-embeddedness, caused by the paralyzing effects of increasing density of ties among clique members can lead to decreasing opportunities for learning and innovation for clique members *(Hagedoorn & Frankort, 2008; Duysters & Lemmens, 2003; Uzzi, 1997).* Firms in a broker position in-between cliques are more likely to escape the negative effect of over-embeddedness by spanning different cliques of firms with a different knowledge base. Thus, in order to attract knowledge with high novelty value, clique-members have a solid motive to look beyond the boundaries of their clique. However, we argue that whether a firm actually succeeds or not in positioning itself in this beneficial network position is determined by its current position in the clique.

We expect that establishing a tie that passes the boundary of the clique is a major step for firms. Firms that are fully embedded within a clique are fully dependent on knowledge flows within this clique. These firms might have a clear incentive to strategically maneuver themselves into a less dependent network position, but these firms are also more dependent on the current knowledge flows within the clique which exerts strong inertial forces preventing these companies from entering into new, more innovative relationships *(Gulati, Nohria & Zaheer., 2000; Duysters & Lemmens, 2003).* Therefore, clique-members have to consider a trade-off between uncertain future returns associated with decreasing its dependence on the clique by establishing a clique spanning tie and the expected costs of endangering the current balance and trust within the clique. Because of this trade-off we expect that firms that are less embedded and less dependent on the knowledge flows within the clique establish relatively more clique spanning ties than clique members that are more embedded within the clique. Therefore, we expect that the formation of clique spanning ties will be positively related to a firm's embeddedness in the clique and argue that:

Hypothesis 4: *Stronger embeddedness in a clique has a negative effect on the number of clique spanning ties.*

5.3 Data and Variables.

Data. Our panel dataset covers the population of ASIC producers over the period 1987-2000. This period captures an important period in the technological development of the ASIC-Industry. Based on the vendor-list included in the ICE ASIC-Outlook industry reports (*McClean, 1987-2000*) we were able to establish a detailed list of all ASIC-producers. Our measures of the technological knowledge bases draw on patent data from the US Patent and Trademark Office[14]. In particular in industries where companies operate on a global scale, such as the ASIC-industry, U.S. patents are a good proxy for companies' worldwide technological performance and technological assets. Our data on strategic technology alliances were obtained from the ICE-industry reports; the ASIC-Outlook reports (*McClean, 1977-2000*) and the MERIT-CATI database on strategic technology alliances (*Hagedoorn, 1993*). Financial data of ASIC producers have been gathered from different sources among which the annual ICE reports (*McClean, 1977-2000*) and COMPUSTAT.

Dependent Variable. In line with Baum, Shipilov & Rowley, (*2003*) and Rosenkopf & Padula (*2008*) we define our dependent variable, clique spanning ties, as relations that involve firms in different cliques. The dependent variable is a count variable - i.e. the number of clique spanning ties in a particular year. Overall, we found 93 such ties in our observation period. We attributed each tie to both firms that established it.

Independent Variables. To test hypothesis 1 we constructed the variable pioneering technology to measure the amount of technological leadership of a firm's technological knowledge base. Following prior research *(Ahuja & Lampert, 2001)* we calculated the variable pioneering technology as the number of patents that cite no other patents. We suggest that the creation of such patents indicate a firms' willingness to adopt a pioneering strategy. To test hypothesis 2 we compute an interaction effect between pioneering technologies and the size of the firm. A firm's portfolio of resources is positively related to its linkage opportunities *(Ahuja, 2000b).* Alliance opportunities originate from social, commercial and technical capital. Thus, larger firms are more appealing as potential alliance partner *(Stuart, 1998).* Large firms have a broader and more diversified established network of alliances *(Hagedoorn & Duijsters, 2002)* and place themselves as dominant firms not only within the clique but also in the overall alliance network. Smaller firms can still induce linkages if they are able to generate beneficial advantages *(Rothaermel, 2002),* such as a radical technological breakthroughs *(Ahuja, 2000b).* It has been argued that small firms

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[14] In order to find those alliances that were established with a clear focus on ASIC technology 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*).

have additional advantages due to their flexibility during periods of radical (technological) change *(Hill & Rothaermel, 2003).* Nevertheless, due to their size benefit, large firms are more likely to establish new alliances and could therefore be expected to establish more clique spanning ties. We calculated this variable based on the natural logarithm of the annual sales of the firm. Before calculating the interaction terms we standardized the variables *(Aiken & West, 1991).* Assuming that there exists a positive correlation between this variable and clique spanning ties, large firms with pioneering technologies will have a higher number of clique spanning ties than their smaller counterparts.

While our last two variables were constructed based on the technological knowledge base of a firm, we constructed hypothesis 3 -experience with clique spanning ties- around the strategic intentions of a firm past alliance behavior. These strategic intentions can be measured by counting the number of clique spanning ties that a firm initiated prior to each observation period. 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 new ties (*see picture 1 for a more detailed list of these options*) we measured a firms prior clique spanning ties as the count of clique spanning ties it formed 5 years prior to the observation year. Hypothesis 4 looks at the effect of a firm's embeddedness within the clique on the formation of clique spanning ties. By maintaining a balanced set of ties within and beyond the scope of the clique firms can minimize their embeddedness inside the clique. This embeddedness can be calculated as a simple count of the number of alliances a firm $_i$ maintains inside and outside clique $_j$. However, a ratio of a firm's inside and outside ties is a more precise indication of a firm's embeddedness on, since a relative measure controls for the relative sizes of each of these particular types of ties. The EI-Index is such a relative measure, designed to calculate a firm's tendency to maintain ties that can be considered as external and internal clique relationships *(Krackhardt & Stern, 1988).* This normalized measure ranges from *-1*, indicating that firm $_i$ is fully embedded in its clique $_j$ because all ties were internal clique relationships, to *+1* indicating that a firm maintains only ties external to the clique[15].

Control Variables*.* We included three firm-level variables, two clique variables, and four dummy variables to control for unobserved effects. To control for unobserved heterogeneity at the firm level we included the variable technological capital to control for the size of a firm's technological knowledge base. Unobserved heterogeneity refers here to the possibility that an unmeasured difference among observationally equivalent firms affects their propensity to establish clique spanning ties. This variable was created by adding

[15] We multiplied the original measures of the EI-calculations by -1, such that higher values represent a higher level of embeddedness.

up the patents that a firm received during the five years prior to the year of observation. Because of the skewness of the data we used the natural logarithm. In order not to loose the 0 observations we added 1 to all observations before calculation the logarithm. A moving window of 5 years is considered as an appropriate time frame for assessing the technological impact *(Podolny & Stuart, 1995; Henderson & Cockburn, 1996).*

The second firm-level variable relates to the centrality of a firm in the overall alliance network. Being located in the center of an alliance network has been recognized as an important and distinctive form of capital of innovating firms *(Gulati, 1995a; 1999).* According to Gulati (*2000*) centrality positively influences a firm's opportunity to form linkages in at least three ways: it serves as a signal of reliability; it serves as a signal of access to other highly embedded firms and it helps to broaden a firm's network horizon. To measure centrality we used the measure of betweenness centrality *(Freeman, 1979).* This measure focuses on the extent to which actor control the shortest paths between other pairs of firms. When a firm has a high score on this measure it can be considered as a firm that dominates the network by controlling large streams of knowledge and information. The third firm-level control variable relates to the absorptive capacity of the firm. Firms that invest more in R&D have broader possibilities to experiment and explore new kinds of technologies. We calculated this variable based on the R&D to sales ratio of each firm.

We used two measures to control for the possible dependence on clique attributes. To measure the effect of the number of cliques a firm participated in on the formation of clique spanning ties we included the logarithm of the number of cliques as a count variable for each clique a firm participated in for each time period. We also calculated clique density as the number of ties that belonged to a clique in a five year window as compared to the maximum number of ties within the clique that could have been formed. Higher density can help govern actions in a group and lead to more cooperative behavior *(Coleman, 1988).*

Furthermore, we include four types of dummy variables to control for different types of contingencies. A first dummy variable was included to control for a potential bias due to the fact that some large companies produce ASIC's only for their internal needs. 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*). Second, sector dummies were included to indicate the sector to which a ASIC-producer belongs. Firms can be exclusively involved in the production of one 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 third dummy variable indicates in which economic region the company is headquartered (*Asia, North America or Europe*), where the default is North America. Finally, year dummy variables were included to capture changes over time in the propensity of companies to establish clique spanning ties. Table 12 provides a detailed overview of all measures that have been used within the empirical analysis.

Table 12: Definitions of dependent and independent variables.

Variable name	Variable description
Clique Spanning tie	Count of the number of clique spanning ties by a firm in year $_{(t)}$
Pioneering Techn.	Number of a firm's patents that cite no other patents $_{(t1-5)}$
Pioneering Techn. * Firm Size	Nr of firm's patents that cite no other patents $_{(t1-5)}$* Logarithm of overall sales of focal firm in year $_{(t1)}$
Experience	Number of prior clique spanning ties $_{(t1-5)}$
Clique embeddedness	Normalized measure of the ratio between internal and external relationships $_{(t1-5)}$
Centrality	Normalized betweenness centrality in alliance network $_{(t1-5)}$
Technological Capital	Logarithm of count of the number of a firm's patents $_{(t1-5)}$
Clique numbers	Logarithm of number of cliques a firm participates in $_{(t1-5)}$
Clique Density	Density of clique in alliance network $_{(t1-5)}$
Firm Size	Logarithm of total overall sales of the focal firm $_{(t1)}$
Firm R&D	Firm total R&D expenditures / Firm overall sales $_{(t1)}$
Captive Producer	Dummy variable denoting that the firm is not selling products on the ASIC-market
GA Producer	Dummy variable denoting that the firm is producing only Standard Cells
PLD Producer	Dummy variable denoting that the firm is producing only PLDs
GA-PLD Producer	Dummy variable denoting that the firm is producing only Gate Arrays and Standard Cells
SC-PLD Producer	Dummy variable denoting that the firm is producing only Gate Arrays and PLDs
GA-PLD Producer	Dummy variable denoting that the firm is producing only Standard Cells and PLDs
GA-SC-PLD Producer	Dummy variable denoting that the firm is producing Gate Arrays and Standard Cells and PLDs
Asian	Dummy variable denoting that the firm is headquartered in Asia
European	Dummy variable denoting that the firm is headquartered in Europe
Annual dummy	Dummy variables denoting the year of observation for the period 1988-2000

5.4 Results.

We use a negative binomial regression model which allows for the variance to exceed the mean *(Hausman et al., 1984).* A random-effects model rather than a fixed-effects model is used as the results of the Hausman specification test indicate that the random effects estimations are consistent and efficient. Table 13 presents the descriptive statistics and the correlation matrix[16] for the different variables. Table 14 shows the results of the random effects negative binomial regression analyses. Model 1 in Table 14, presents the results for the baseline model which includes only a set of control variables. Model 2 adds the variable pioneering technology, and model 3 adds the interaction between explorative technologies and firm size. Model 4 includes the variables experience and embeddedness which are associated with a firm's network position. Finally, models 5 and 6 present the full model incorporating all variables associated with a firm's technological knowledge base and network position.

Our first hypothesis related to pioneering technologies in a firm's technological knowledge base is included in model 2 as a first explanatory variable. We find strong support for hypothesis 1 and adding this variable also improves the overall fit and significance of the model. Firms with pioneering technologies have more opportunities to establish ties between different cliques. In model 3 we include the interaction term between the attractiveness of a firms' technological knowledge base and firm-size in order to understand how firm size moderates the relationship between pioneering technologies in a firm's technological knowledge base and the formation of clique spanning ties. The positive and significant coefficient of the interaction term supports hypothesis 2 and indicates that the impact of pioneering technology in a firm's technological knowledge base on the formation of new clique spanning ties is significantly stronger for larger firms. The main effect of pioneering technologies is no longer statistically significant indicting that small firms do not profit from pioneering technologies in their patent portfolio to establish clique spanning ties. This result may point to the fact that large companies with an attractive technological portfolio have reputation effects and alliance capabilities that allow them to establish alliances with new partners beyond the clique in which they are embedded. Adding the interaction effect in model 3 increases the fit and significance of the model even further.

Model 4, which adds two extra variables, shows a strong improvement over the baseline model. In model 4, we find support for hypotheses 3 indicating that firms with more prior experience with the formation of clique spanning ties have

[16] Given the relatively high correlation between some variables, alternative models have been estimated as a robustness check dropping one of the correlated variables at a time (*Sampson, 2007*). As results are nearly identical to those presented a preference is given to the model that includes all variables since dropping these variables could lead to omitted variable bias.

a better ability in the formation of clique spanning ties. Similarly, firms that are highly embedded within the clique are less likely to establish clique spanning ties, which is in support of hypothesis 4. This indicates that a firm's prior network actions and its position in the clique should be considered when explaining a firm's propensity to establish ties that cross clique boundaries. Models 5 and 6 present a full model including all variables associated with a firm's technological knowledge base and network position. Model 5, which includes pioneering technologies and the network variables, indicates that the effect of pioneering technologies remains significant when adding the variables associated with a firm's network position. Adding the interaction between pioneering technologies in a firm's technological knowledge base and firm size to Model 6 increases the significance of the model. Just as in model 3, the main effect of pioneering technologies is no longer significant, while the interaction effect and estimates related to a firm's network position exert a significant influence on the formation of clique spanning ties.

The control variable associated to the size of a firm's knowledge base is not significant which implies that the size of the technological knowledge stock does not induce a firm to establish more clique spanning ties. Furthermore, a firm's centrality in the overall network does not have an important effect on the establishment of clique spanning ties. This finding is interesting in itself because it indicates that having a central location does not lead to these specific types of network action. The establishment of clique spanning ties is in that respect different than the establishment of other ties, where centrality does plays an important role in explaining new tie formation *(Gulati & Garguilo, 1999).* In all models, the clique-level variables do not have an impact of the establishment of new clique spanning ties. These clique level effects were used to control for the possibility of unobserved variances in clique attributes. Furthermore, manufacturers that produce standard-cells and PLDs at the same time establish, relatively more clique spanning ties, compared to other ASIC-sub segments. This finding indicates that clique spanning partnering behavior is not homogenous for the whole ASIC-industry. Finally, R&D intensity and technological capital does not increase the probability that a firm will establish clique spanning ties. The fact that these two variables do not have a significant effect on clique spanning ties formation suggests that the quantity of the post and current technological investments do not play a role. We find that the quality of the technological portfolio creates incentives to partner with firms outside its own clique. This also explains why pioneering technology has a strong and positive impact on the probability to establish clique spanning ties.

Table 13: Descriptive statistics and correlation matrix.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Clique Sp. T.	1.00																		
2	Pion. techn.	0.16	1.00																	
3	Experience	0.15	0.27	1.00																
4	Clique emb.	0.13	0.14	0.51	1.00															
5	Centrality	0.11	0.10	0.56	0.62	1.00														
6	Techn.Cap.	0.12	0.30	0.40	0.36	0.26	1.00													
7	Clique Nrs.	0.08	0.21	0.65	0.64	0.70	0.35	1.00												
8	Clique Dens.	0.01	0.05	0.24	0.22	0.22	0.12	0.45	1.00											
9	Firm Size	0.08	0.22	0.26	0.23	0.23	0.43	0.30	0.01	1.00										
10	Firm R&D	-0.01	-0.12	-0.07	-0.05	-0.06	-0.19	-0.07	0.07	-0.68	1.00									
11	Captive	-0.03	-0.10	-0.07	-0.18	-0.14	-0.02	-0.07	-0.06	0.31	-0.19	1.00								
12	GA	-0.07	-0.06	-0.20	-0.28	-0.21	-0.28	-0.25	-0.08	-0.21	0.13	-0.06	1.00							
13	PLD	-0.02	-0.06	-0.06	0.03	-0.11	0.22	-0.08	0.06	-0.44	0.35	-0.16	-0.11	1.00						
14	GA-PLD	-0.01	0.09	0.07	0.07	-0.03	0.15	0.06	-0.02	0.41	-0.37	0.10	-0.26	-0.31	1.00					
15	SC-PLD	0.09	0.05	0.10	0.10	0.20	0.02	0.18	0.08	0.01	0.04	-0.06	-0.03	-0.04	-0.10	1.00				
16	GA-PLD	0.04	-0.04	-0.00	0.02	0.05	0.10	0.03	0.04	0.03	0.06	-0.07	-0.05	-0.05	-0.13	-0.02	1.00			
17	GA-SC-PLD	0.09	0.05	0.26	0.29	0.46	0.13	0.33	0.07	0.17	-0.10	-0.17	-0.11	-0.14	-0.33	-0.04	-0.06	1.00		
18	Asian	-0.02	0.21	-0.05	0.01	-0.14	0.07	-0.14	-0.17	0.41	-0.41	-0.12	-0.04	-0.21	0.47	-0.07	-0.09	-0.10	1.00	
19	European	-0.03	-0.08	0.06	0.08	0.23	-0.19	0.33	0.15	0.12	-0.01	0.15	-0.10	-0.17	0.01	-0.05	0.09	0.07	-0.27	
	Mean	0.24	0.10	1.08	0.25	4.11	1.68	0.93	0.35	7.84	0.11	0.17	0.82	0.12	0.43	0.12	0.22	0.13	0.25	0.18
	S.D.	0.50	0.34	1.19	0.49	5.16	1.19	0.87	0.85	2.70	0.07	0.37	0.28	0.32	0.50	0.11	0.15	0.34	0.43	0.39
	Minimum	0.00	0.00	0.00	-0.54	0.00	0.00	0.00	0.14	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Maximum	3.00	2.00	8.00	1.00	28.96	5.65	2.99	0.57	12.01	0.67	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 14: Determinants of Clique Spanning Ties of ASIC producers: 1987 – 2000.

	(1)	(2)	(3)	(4)	(5)	(6)
Pioneering Techn.		0.56 (0.21)***	-0.81 (0.75)		0.47 (0.20)**	-0.73 (0.72)
Pion. techn. * Firm Size			0.26 (0.13)**			0.23 (0.13)*
Experience				0.22 (0.09)**	0.18 (0.09)**	0.15 (0.09)*
Clique embeddedness				-0.52 (0.26)**	-0.54 (0.26)**	-0.56 (0.26)**
Centrality	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)	-0.03 (0.02)	-0.02 (0.03)	-0.03 (0.03)
Technological Capital	0.17 (0.12)	0.10 (0.13)	0.12 (0.13)	0.16 (0.12)	0.10 (0.12)	0.12 (0.12)
Cliques numbers	0.06 (0.18)	-0.03 (0.19)	-0.05 (0.19)	-0.13 (0.19)	-0.20 (0.19)	-0.22 (0.19)
Cliques density	-1.68 (1.30)	-1.47 (1.30)	-1.33 (1.29)	-1.52 (1.25)	-1.26 (1.25)	-1.21 (1.25)
Firm Size	0.10 (0.07)	0.09 (0.07)	0.08 (0.07)	0.08 (0.07)	0.07 (0.07)	0.06 (0.07)
Firm R&D	2.01 (1.79)	1.96 (1.81)	1.94 (1.78)	1.58 (1.68)	1.50 (1.71)	1.51 (1.70)
Captive	-0.38 (0.32)	-0.26 (0.32)	-0.14 (0.31)	-0.22 (0.28)	-0.12 (0.29)	-0.03 (0.29)
GA	-0.43 (0.49)	-0.41 (0.49)	-0.38 (0.49)	-0.38 (0.48)	-0.35 (0.48)	-0.30 (0.48)
PLD	-0.10 (0.43)	0.07 (0.44)	0.15 (0.43)	-0.15 (0.40)	-0.01 (0.41)	0.07 (0.41)
GA-PLD	-0.00 (0.29)	0.12 (0.30)	0.25 (0.30)	-0.07 (0.27)	0.05 (0.27)	0.19 (0.28)
SC-LD	0.29 (0.65)	0.40 (0.64)	0.83 (0.67)	0.70 (0.56)	0.77 (0.56)	1.13 (0.59)*
GA-PLD	0.24 (0.58)	0.42 (0.58)	0.52 (0.58)	0.19 (0.53)	0.38 (0.54)	0.49 (0.55)
GA-SC-PLD	0.20 (0.37)	0.34 (0.37)	0.58 (0.38)	0.10 (0.32)	0.25 (0.33)	0.52 (0.35)
Asian	-0.28 (0.31)	-0.40 (0.31)	-0.36 (0.30)	-0.24 (0.28)	-0.34 (0.29)	-0.33 (0.29)
European	-0.15 (0.32)	-0.16 (0.33)	-0.13 (0.33)	-0.07 (0.29)	-0.08 (0.29)	-0.05 (0.29)
Constant and year	Included	Included	Included	Included	Included	Included
Observations (firms)	643 (80)	643 (80)	643 (80)	643 (80)	643 (80)	643 (80)
Log Likelihood	352,71	349,48**	347,13,**	348,03***	345,51**	343,48**
Baseline model		Model 1	Model 2	Model 1	Model 3	Model 5

Table shows results of random effects negative binomial model
Note 1: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$
Note 2: Standard Deviations in Parentheses

5.5 Discussion and Conclusions.

Firms face increasing challenges in today's technological and competitive environment. Especially within high tech industries, they cannot afford a closed innovation model and increasingly choose to balance internal and external sources of innovation, with alliances as one of the major governance modes to source external innovations. Besides a few notable exceptions *(Baum, Shipilov & Rowley, 2003; Duysters & Lemmens, 2003; Gomes-Casseres, 1996; Rowley et al., 2004, 2005; Rosenkopf & Padula, 2008),* research exploring the effects of external and internal alliance network characteristics on alliance network change at the clique level of analysis has been ignored so far. While most studies have shown motives why firms tend to be locally biased and path-dependent in their search strategies *(Gulati, 1995a; Stuart & Podolny, 2000; Walker, Kogut & Shan, 1997),* relatively less is known about situations in which firms may opt for forming these clique spanning ties. To our knowledge, no research has focused yet on the effects of a firm's technological knowledge base and prior network position in the clique on the formation of new clique spanning ties. This perspective is interesting in order to get a better insight in the relation between technological portfolios and alliance strategies. The empirical value of this line of research is determined by whether cliques are also real life artifacts *(Rowley et al, 2005).* While we were able to empirically show the existence of cliques, clique spanning ties and their underlying mechanisms, we were not able to describe the full underlying motivation of managers engaging in these clique spanning ties. Future research could experiment with survey methods focusing on alliances and alliance networks *(Lane & Lubatkin, 1998)* in order to get a more accurate insight in the motives and rationales of ties that span clique boundaries.

Based on our empirical results we found support for the fact that firms have a tendency to work together in locally clustered groups of firms, but that some firms try to bridge two groups by forming clique spanning ties. We found evidence of a strong positive relationship between a firm's involvement in pioneering technologies and the number of newly established alliances that cut across cliques. This finding indicates that the amount of pioneering technologies within a firm's technological knowledge base is an important indicator of a firm's potential to go beyond local search in an alliance network. Furthermore, we found that this effect is moderated by the size of a firm, indicating that larger firms have more potential to use the technological leadership in forming clique spanning ties. Within this industry, it is not the size of a firm's technological knowledge base but the quality of a firm's technological knowledge base that explains the effect between a firm's technological knowledge base and the formation of clique spanning ties. Prior network position was also found to be an important indicator of a firms potential to form clique spanning ties. Not the position in the overall network itself, but prior experience with the establishment of clique spanning ties and the level of embeddedness within a group determines a firms' clique spanning potential. Firms that are not heavily embedded in the clique formed significantly more clique spanning ties than their more embedded counterparts. Together these research findings indicate that a firm's potential to go beyond local search within an alliance network is influenced by factors that are both external and internal to the existing alliance network.

Our research contains a number of limitations, which in turn suggest several new paths for future research. In line with prior research on alliance behavior of clique members, we limited our attention to the antecedents of ties that cut across cliques *(Baum, Shipilov & Rowley, 2003; Rosenkopf & Padula, 2008).* On the one hand, this line of research could be extended by deepening our knowledge about these and complementary antecedents of clique spanning ties e.g. clique spanning ties might have different functions in turbulent times or in different stages of the technology life cycle which might stimulate firms to look beyond the current clique members as technological partners. On the other hand, our knowledge on the antecedents of the other forms of network evolution at the clique level such as the formation of "inside clique ties", "outside clique ties" and even the entry of new firms to the main component is still underdeveloped *(Rosenkopf & Padula, 2008).* Furthermore, while prior research indicates that strategic advantages can be reached by being located within embedded clique structures *(Rowley et al., 2004; Lazzarini, 2007),* relatively little is known how a clique strategy and network evolution at the clique level influences a firms *innovative* performance. Therefore, many interesting questions concerning cliques as an independent variable remain unanswered: Are clique member's better innovators – all else equal – than non-clique members? Can clique members improve their innovative performance by establishing cliques spanning ties or outside ties, or is a combination with inside ties a better strategy? Do cliques spanning ties have a particular role to play in explorative or explorative innovation?

In this paper we focused on cliques and clique spanning ties, i.e. those ties that enable clique members to go beyond local search and tap into the resources of other cliques. Especially in knowledge intensive industries, alliance strategies are largely driven by establishing access to non-redundant sources of knowledge *(Letterie, Hagedoorn, Kranenburg & Palm, 2008).* This research paper is a first attempt to deepen our knowledge on network evolution and dynamics by investigating the effects of a firm's technological knowledge base on the formation of ties beyond local search.

Chapter 6: Discussion and Conclusions

6.1 Introduction.

This dissertation is part of the research theme on how alliance networks emerge and evolve over time and investigates how these network dynamics influence the innovative performance of the embedded firms. The particular contribution of this dissertation to this growing body of research is that it moves beyond the most commonly used types of alliance network embeddedness and explores the causes and consequences coming from a firm's clique-embeddedness. Recently, empirical research on the causes and consequences of cliques-embeddedness gained new momentum within the managerial literature *(Baum, Shipilov & Rowley, 2003; Lazzarini, 2007; Padula, 2008 Rosenkopf & Padula, 2008).* While these manuscripts provide a good overview regarding the reciprocal relationship between alliance network dynamics and performance from a clique perspective, important research questions about the underlying dynamics of clique-embeddedness in relation to its innovative performance still remain unanswered. Within this dissertation two related sections have been explored in order to extent our current knowledge about the underlying dynamics of clique-embeddedness. The first section studied the relationship between clique-membership and *innovative* performance while the second section investigated exogenous and endogenous drivers of network change from a clique-perspective. Hence, this dissertation explored these underlying dynamics by answering the following research question:

> *How do network positions and technological portfolios influence the innovative performance of clique-members and how can clique-members reposition themselves beyond the scope of their clique?*

The goal of this concluding chapter is to indicate how the results of the current dissertation contribute to this bourgeoning field of knowledge. First, an overview of the main findings of each of the preceding empirical chapters will be presented. Next, a discussion follows regarding the implications of these findings from a theoretical and a practical point of view. This chapter will conclude with a reflection on the current study and directions for future research.

6.2 Main research findings.

In line with alliance networks in other high-tech industries *(Verspagen & Duysters, 2004; Schilling & Phelps, 2007; Rosenkopf & Padula, 2008; Watts, 1999)*, the ASIC-industry shows small world characteristics *(Watts, 1999).* This makes the ASIC-industry an appropriate industry to study as it indicates that the alliance network is sparsely connected and locally clustered. The current research was split up into two separate but related research themes. The first section explored several antecedents of innovative performance stemming from firms' embeddedness within clique(s). Hence, this section used innovative performance as the variable of interest. Chapter 3 explored the influence of clique-embeddedness on innovative performance and refined this causal link by looking at the mediating effect of companies' position within the clique. Chapter 4 explored another mechanism that influences clique-members ability to reap the benefits of their clique-membership: the (in) ability of clique-members to adapt to technological changes. The second section, which includes chapter 5, focused on network dynamics as the variable of interest. This chapter extends our current knowledge about the exogenous and endogenous drivers of new tie formation by looking at the antecedents of clique-spanning ties. The key findings of these chapters are summarized and will be discussed below.

Section 1: Clique-embeddedness and innovation.

This section focused on the relationship between clique-membership and *innovative* performance. Within this section two conditions have been addressed which explain variations between clique-members ability to improve its innovative performance. Overall, the results indicate that clique-membership does enhance innovative performance, but also indicate that not all that glitters is gold for all members of the clique. Significant variations are observable between clique-members innovative performance which arises from (*1*) its position inside the clique and (*2*) companies' (in) ability to adapt to technological changes.

Chapter 3: Position in the clique.

This chapter focused on the effects of network positions within the clique on the innovative performance of clique-members. Past research indicates that embeddedness within the alliance network affects innovative performance *(See Freeman, 1991; Meeus, Oerlemans & Kenis, 2008; Pittaway et al., 2004 for reviews).* Conversely, if and how clique-embeddedness influences innovative performance remains unknown. A key finding of this chapter is that clique-embeddedness does stimulate innovative performance of the embedded firms. This is in line with other empirical studies that found positive effects of clique embeddedness on financial and operational performance *(Lazzarini, 2007; Rowley et al., 2004).* However, significant variation arises from companies' position within the clique. First, the most prominent companies inside the clique profit relatively more from their clique-embeddedness than companies that are less prominent within the clique. Second, companies that are less embedded inside their clique profit more than companies that are more embedded within their clique. Last, companies that established more clique-spanning ties profit more than companies that established less clique spanning ties. However, there is an optimum to the number of clique spanning ties that contribute to the innovative performance of clique members: we found an inverted U-shape relation between clique spanning ties and innovative performance. Together these findings indicate that a clique-strategy is a viable strategy to increase innovative performance. Companies should seriously consider their position within the clique as the benefits of clique-embeddedness are unevenly distributed.

Chapter 4: The (in) ability to adapt to technological changes.
This chapter looked at the technological overlap of companies that are embedded in the same clique and innovative performance of clique-members during technological changes. Past research indicates that companies become technologically more similar when they cooperate intensively *(Brass, Butterfield & Skaggs, 1998; Mowery, Oxley & Silverman, 1996).* Over time, this could endanger the potential for novelty creation and innovation within the clique, which could become a serious threat for companies' innovative performance during periods of technological uncertainty *(Christensen, 1997; Christensen & Raynor, 2003).*

A key finding of this chapter is that the knowledge bases of clique-members are indeed more similar than the knowledge bases of companies that are embedded in different cliques. Furthermore, companies are significantly better off with the formation of a clique spanning tie when searching for novel knowledge and technologies than with the formation of an inside clique tie. Both the formation of inside clique ties and clique spanning ties has a positive effect on innovative performance. Nonetheless, the effect of clique spanning ties is stronger than that of inside clique ties. Another key finding is that empirical evidence did not support the notion that clique-embeddedness is less beneficial during periods of technological change. Yet, while the formation of past inside clique ties did not affect companies' innovative performance during technological turbulent periods, the formation of past clique spanning ties had a positive influence.

Section 2: Micro dynamics of network evolution.
This section used alliance network dynamics as the variable of interest and explored how endogenous and exogenous factors affect clique-members' ability to reposition themselves beyond the scope of the clique. Repositioning is important as it allows clique-members to access novel sources of knowledge and technology. Furthermore, clique spanning ties allow companies to broker knowledge and technologies between two cliques with relatively large pools of knowledge and technology. While most studies have shown motives why firms tend to be locally biased and path-dependent in their new tie formation *(Gulati, 1995a; Stuart & Podolny, 2000; Walker, Kogut & Shan, 1997)*, relatively less is known about the underlying dynamics of new tie formation that span the boundaries of dense cliques in alliance networks.

Chapter 5: Going beyond local search.
This chapter looked into the antecedents of clique spanning ties. While prior studies indicated that companies' position in the alliance network determines its

opportunities to establish clique spanning ties *(Baum, Shipilov & Rowley, 2003; Rosenkopf & Padula, 2008)*, no insights are available about the role of companies' technological knowledge bases as a driver of the establishment of clique spanning ties. A key finding of this chapter is that companies' knowledge base is an important indicator of its potential to establish clique spanning ties. There is a strong positive effect of a technological portfolio that includes pioneering technologies on companies' ability to form clique spanning ties. Yet, this effect is moderated by the size of the company, indicating that larger firms are better equipped to establish clique spanning ties when their knowledge base is attractive to outsiders. Furthermore companies' network position does also influence the ability to form clique spanning ties. Not their position in the overall network, but their position within the clique (*companies that are more embedded form less clique spanning ties*) and experience with prior clique spanning ties determine their ability to form clique spanning ties. Together these research findings indicate that companies' knowledge base and its position within the clique are significant predictors of companies' ability to form clique spanning ties.

6.3 Research implications.

Apart from the individual contributions of these three empirical chapters, the findings of this dissertation also contribute to the managerial literature in several distinctive ways.

First, the current study contributes to the broader literature on network embeddedness and economic action *(Granovetter, 1985)*. A widely accepted view within literature studying the antecedents of innovation is that network embeddedness increases the innovative performance of companies *(Ahuja, 2000a; Duysters & Lemmens, 2003; Gulati & Garguilo, 1999; Hagedoorn & Schakenraad, 1994; Vanhaverbeke et al., 2008; Zollo, Reuer & Singh, 2002)*. Yet, while the importance of embeddedness starts to become well known from the perspective of ego-network embeddedness *(Ahuja, 2000a; Baum, Calabrese & Silverman, 2000; Capaldo, 2007; Shan, Walker & Kogut, 1994; Smith-Doerr et al., 2002; Stuart, 2000; Vanhaverbeke et al., 2008)* and even from the perspective of embeddedness in the overall industrial-network *(Rowley, Behrens, Krackhardt, 2000; Shilling & Phelps, 2007)*, we know relatively less about the influence of clique-level embeddedness on companies' innovative performance. The current study contributes to this line of literature and results indicate that clique-embeddedness does positively affect companies' innovative performance. However, significant variation arises as not all firms are able to benefit equally all the time. Companies' ability to benefit from clique-embeddedness is influenced by contingencies such as position within the clique, past alliance behavior, and it's (in)ability to adapt to technological shifts. In this way, this dissertation contributes to our knowledge about the broader literature on network embeddedness and economic action by exploring the antecedents of innovative performance from a clique perspective.

Second, this research contributes to the rising theme on how alliance networks emerge and evolve over time by investigating the dynamics coming from companies' clique-embeddedness. Research on clique-embeddedness and innovative performance has demonstrated that the benefits of clique-embeddedness are unevenly distributed as some companies have better access to knowledge and technologies *(Krackhardt, 1992; Burt, 2000).* However, whether these favorable positions are the outcome of companies actively searching for access to valuable knowledge and technologies or merely the by-product of other forces is still unclear *(Rowley & Baum 2008)*. Therefore section 2 in this dissertation explored the role of companies' technological knowledge base as a driver of new tie formation since companies' technological knowledge base might be one of the reasons why companies end-up in these favorable positions within the alliance network in the first place. One of these favorable positions within the alliance network is when companies' are able to form a bridge between two densely connected regions in the alliance network, allowing them control knowledge and technology flowing between these regions *(Burt, 2007)*. Yet, while most studies have shown that companies' tend to be locally biased and path-dependent by forming new alliances with familiar partners *(Gulati, 1995a; Stuart & Podolny, 2000; Walker, Kogut & Shan, 1997)*, we know relatively less about the conditions underlying the formation of new alliance with more distant partners like those embedded in other cliques. The current study contributes to this line of literature by providing empirical evidence that companies' ability to form clique spanning ties is determined by the attractiveness of its own knowledge and technology and by its position within the clique.

Third, despite the apparent frequency with which R&D inter-firm networks are observed to show small world characteristics -i.e. sparsely connected and locally clustered- *(Verspagen & Duysters, 2004; Schilling & Phelps, 2007; Rosenkopf & Padula, 2008; Watts, 1999),* there is little empirical evidence that addresses the question how clique structures affect micro-level behavior and vice versa. Understanding the causes and consequences of the micro-dynamics from a clique-perspective could improve our overall understanding of the evolution of complex macro-level structures such as the small world *(Rosenkopf & Padula, 2008).* Baum et al (*2005 p.516*) concluded that their study "shows that there is a downward causation from clique-level attributes, and upward causation from clique-member attributes, and that both sets of causal paths are consistent". Hence, this shift in focus to the clique has the potential to link multiple levels of analysis within social network literature *(Brass et al., 2004; Hagedoorn, 2006)*, and has the potential to explain network dynamics more accurately as it distinguishes between various types of new tie formation. For example, findings by Rosenkopf

& Padula (*2008, p.15*) indicate "that different dynamics describe alliance formation within, between, and beyond local clusters." The current study contributes to this line of literature by describing the antecedents of alliance formation between cliques, which increases our understanding about the overall theme of how alliance networks emerge and evolve over time.

Fourth, this dissertation also has implications for research on brokerage and closure *(Coleman, 1988; Burt, 1992).* The inclusion of clique topology in these theories allows us to discern more beneficial network structures for companies embedded in cohesive regions. Contemporary insights advocate for the importance of so-called hybrid networks "that resemble locally clustered, sparsely connected small world structures *(e.g. Watts, 1999),* in which closure and bridging are viewed as complements that support coordinated action and create advantages *(Rowley & Baum 2008, p.3)".* Empirically, this observation is supported by the study of Schilling & Phelps (*2007, p.1124*) who state that "both local density and global efficiency can exist simultaneously, and it is this combination that enhances innovation", and by Padula (*2008, p.12*) who demonstrates that "cohesive and sparse alliances play complementary roles in supporting firm innovation, each adding to the value of the other, and that firms combining both cohesive and sparse relationships in their alliance portfolio show higher rates of innovation than those which employ either pattern of collaborative agreement alone". The current study contributed to this line of literature by providing empirical evidence that clique-members that established more clique-spanning ties in the past are more innovative than clique-members lacking these beneficial relations.

Fifth, the use of the clique construct allowed determining the antecedents of exploratory activity with distant firms in the alliance network and therefore also speaks to the literature on organizational learning *(Argyris & Schon, 1978)* and explorative and exploitative learning in particular *(March, 1991)*. Alliances are important vehicles for exploring new knowledge and technologies as alliances allow companies to bridge technological domains effectively *(Rosenkopf & Almeida, 2003).* However, establishing new ties highlights a trade-off because access to more novel knowledge and technology via forming ties beyond local search is available at the expense of the governance mechanisms, which are created by trust and familiarity *(Rosenkopf & Padula, 2008).* The current study contributes to this line of literature that examines the antecedents of exploratory activity with distant firms, by incorporating a clique perspective *(Baum, Shipilov & Rowley, 2003; Rosenkopf & Padula, 2008).* It looked at the attractiveness of a firm's knowledge base and companies' position within the clique as a predictor of ties beyond local search.

6.4 Reflection and recommendations for future research.

While the current study provides interesting insights into the conditions that influence the innovative performance of clique-members and how clique-members can reposition themselves beyond the scope of their clique to improve their innovative performance, it also dealt with limitations which provide interesting avenues for future research.

A first avenue for future research relates to the first section which explored antecedents of innovative performance stemming from companies' embeddedness within clique(s). This line of research has ample room for additional empirical contributions. This dissertation was able to show that companies are able to increase their innovative performance via embeddedness within cliques, but did not provide evidence that all types of learning and innovate activity are improved by this strategy. Clique-members might have different strategies for different types of learning. Linking the configuration of the clique with various types of learning and innovative outcomes would be a valuable contribution to the literature. For example, Vanhaverbeke et al., (*2008*) found evidence that the configuration of companies' ego-network, in terms of redundancy and density, affects companies' ability to create technologies in core areas *(exploitation)* and/or non-core areas *(exploration).* This view could also be applicable towards the configuration of the clique as some cliques might outperform other cliques and hence provide more positive externalities. This dissertation did not control for these variations that could arise from the configuration of the clique and for different types of learning and innovative outcomes. Variations that could arise from the configuration of the clique can result from for example cliques' size, density, age *(Baum, Shipilov & Rowley, 2003; Rowley et al., 2004, 2005)* and attractiveness of the accessible knowledge and technologies within the clique. These variations could also result in different types of learning and innovative outcomes as some clique-configurations and companies' position therein can affect companies' ability to explore new fields of knowledge and technologies *(Jaffe, 1986)* and to produce innovations that are more radically new to the industry *(Ahuja & Lampert, 2001).*

A second avenue for future research relates to the second section which investigated exogenous and endogenous drivers of network change from a clique-perspective. This line of research also has ample room for additional empirical contributions. This dissertation was able to show some of the antecedents of clique spanning ties *(Baum, Shipilov & Rowley, 2003; Rosenkopf & Padula, 2008),* but a wider set of antecedents, as well as a wider set of network changes, could be observed by incorporating a clique-perspective. The potential of this line of research has been described by Rosenkopf & Padula (*2008, p.15*) who stated that "different dynamics describe alliance formation within, between, and beyond local clusters". Hence, this line of research could be extended on the one hand by deepening our knowledge about the dynamics underlying new tie formation from a clique-perspective e.g. the use of clique spanning ties might vary under different conditions within the external (*technological*) environment. On the other hand this line of research could be extended by broadening our knowledge about the antecedents of other forms of network evolution at the clique level such as the formation of "inside clique ties", "clique spanning ties" and even the entry of new firms to the main component *(Rosenkopf & Padula, 2008),* e.g., there might be different dynamics arising from companies' knowledge and technology portfolios underlying these different types of ties altogether.

A third avenue for future research arises from the potential that other estimation methods can bring to this line of research. Recent methodological advancements in network literature such as *p** models *(Wasserman & Pattison, 1996)* make it possible "to assess whether certain ties or network configurations have greater probabilities of being observed based on theoretical hypothesized properties *(Contractor et al., 2006 p.9)"*. Another option would be to adapt the unit of observation from "firm-year" observations towards "dyad-year" observations *(See Pittaway, 2004 for a review).* The "firm-year" observation has a long tradition within alliance network research *(See Meeus et al., 2008 for a review)* but this method also has some shortcomings as it uses firm-year averages without being able to discriminate some of the main effects. For example, using a dyad-year observation would allow estimating the antecedents of new tie formation more accurately on some indicators as it is able to incorporate a more accurate set of partner attributes. Even a "clique-year" perspective could be an interesting pathway for future research in order to determine forces that are able establish or destroy cliques, or to investigate the antecedents of clique-performance.

A fourth avenue for future research arises from the one-sector research design. While limiting the study to a single sector has the advantage of identifying and describing the relevant processes in more depth, it also has it costs as a single-industry study leads to a decrease in terms of generalization of the empirical data. Hence, one should be wary to some of the dynamics and characteristics that are unique to this industry which might influence our empirical results. The ASIC-industry is a typical high-tech industry in which *innovative* success depends on the ability to get timely access to novel technological developments and valuable flows of knowledge. Within the ASIC-industry, barriers to enter are reasonably high since the industry is very knowledge intensive, has a strong IP regime, and the design and production of ASIC's require high investment costs. The industry is dominated by large integrated companies with only some that adopted a focused strategy. Hence, studying how network positions and technological portfolios influence the innovative performance of clique-members and how clique-members reposition themselves beyond the scope of their clique within *other high-tech industries* might lead to other results when these industries differ on one of these characteristic aspects of the ASIC-industry. Furthermore, this study is one of the first to explore the effects of cliques from the perspective of a high-tech sector. Replicating this study within *medium of low-tech industries* could further increase our understanding regarding how specific industry conditions affect the empirical results. The existence of cliques has been reported by various studies *(Baum, Shipilov & Rowley, 2003; Lazzarini, 2007; Padula, 2008; Provan & Sebastian, 1998; Rowley et al., 2004, 2005)* and cliques improve performance in various industries such as health care *(Provan & Sebastian, 1998),* micro-processors *(Gomes-Casseres, 1996),* airline operations *(Lazzarini, 2007)* and investment banking *(Rowley, 2004).* However, compared to high-tech sectors, the acquisition of external knowledge and technologies is a less important driver of clique-embeddedness within these industries. Hence, it would be equally interesting to replicate this study within these industries, especially to investigate the effects of position in the clique and environmental turbulence on performance within these industries.

Fifth, within the empirical analysis, data has been used within the period 1987 – 2000. This decision was mainly driven by empirical considerations since the measure of innovative performance is very sensitive to right censoring when used as a dependent variable. Within this dissertation, innovative performance is measured as a weighted patent count, which gives older patents a higher likelihood to receive citations compared to younger patents. In order to correct for this right censoring a simulated cumulative distribution lag was applied (*Hall, Jaffe & Trajtenberg 2001).* Chapter 5 included an independent variable that made use of patents as an indicator of innovative performance. However, this measure was less sensitive to right censoring since companies' patents had to be granted in order to be incorporated within this variable[17]. Since the benefit of two additional observation years did not countervail against the time investment to collect all relevant data, the same dataset and time period has been used. While this empirically explains why limiting this study to the time period 1987 – 2000 is appropriate, it does not provide sufficient insight regarding the more recent developments within this industry. While the industry is an extremely dynamic and turbulent, no indications were found that the industry experienced major transitions after 2000. The documents that have been studied for the purpose of this study did observe dynamics within the industry regarding the economic downturns in 2001 and 2009; observed that large integrated companies' spun off their semiconductor divisions due to the cyclical nature of the semiconductor industry (*e.g. Philips; NXP, Siemens: Infineon*); and observed that companies progressively patented their inventions as an IP licensing became an

[17] Currently, the USPTO only discloses all relevant information on patents granted until the end of 2005. As one should consider that an average time lag of 3 years is applicable, this study could have contained a maximum of 2 additional observation years with reliable data.

increasingly lucrative strategy. However, these findings provide no clear argumentation to consider that the reciprocal relationship between innovation and companies' alliance behavior have been affected by these dynamics.

Sixth, within this dissertation social network theory is used to hypothesize about the main research questions regarding the reciprocal relationship between innovation and companies' alliance behavior from a clique perspective. A social network theoretical view allows hypothesizing beyond the strategic benefits of one single business relation, as the characteristics of all relationships within the alliance network are taken into consideration within this theoretical perspective (*Gulati, Nohria & Zaheer, 2000*). Especially within high-tech industries, innovative success depends on the ability to get timely access to novel technological developments and valuable flows of knowledge. Hence, companies that strategically design their alliance network are better positioned to benefit from these network effects as technological spillovers occur relatively more within certain parts of the alliance network. However, the antecedents of knowledge spillovers are diverse and can be studied from various theoretical perspectives. Besides market-transactions and alliances, companies have various options to benefit from incoming knowledge spillovers (*Cassiman & Veugelers, 2002; 2007*). Hence, besides profiting from knowledge spillovers induced by alliances and clique-membership, companies also profit from informal forms of knowledge spillovers that occur within the clique. Therefore, studying cliques from the perspective of social network theory might have resulted in unobserved effects regarding knowledge spillovers which could become visible when studying cliques from other theoretical perspectives.

Last, and perhaps most important, "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, Shipilov & Rowley, 2003).* While we were able to empirically show the existence of cliques, clique spanning ties and their underlying mechanisms, we were not able to describe the full underlying motivation and awareness of managers engaging in these clique spanning ties. Future research could experiment with case studies or survey methods *(Lane & Lubatkin, 1998)* in order to get a more accurate insight in the motives and rationales of their participation in cliques and the perceived value of clique spanning ties. Furthermore, the current study followed Rowley et al., (*2005*) and was limited to a technique that detected overlapping cliques. Companies' position inside the clique as well as its past alliance behavior is therefore dependent on the ability of the procedure to precisely ascribe the right processes towards the focal firms and their alliances. Empirically, various studies also used non-overlapping techniques to detect cliques such as structural equivalence *(Baum, Shipilov & Rowley, 2003; Rowley et al., 2004; Rosenkopf & Padula,* *2008; Padula, 2008; Vanhaverbeke & Noorderhaven, 2001)* and tabu search *(Lazzarini, 2007).* While there are valid theoretical motivations underlying the decision to use N-Clan as the proper clustering technique, it would be interesting from a methodological perspective to further explore the consequences of using different techniques for determining variables such as clique boundaries, clique participants, and new tie formation in terms of their structural property, i.e. clique spanning tie, inside clique tie, etc.

The avenues for future research presented above are by far an exhaustive enumeration of potential future research options and the body of this dissertation is by far exhaustive regarding the reciprocal relationship between alliance network dynamics and innovation from a clique-perspective. Despite these shortcomings, the current study does advance current knowledge in distinct ways and evokes more interesting questions to be asked.

Appendix 1: Semiconductor manufacturing

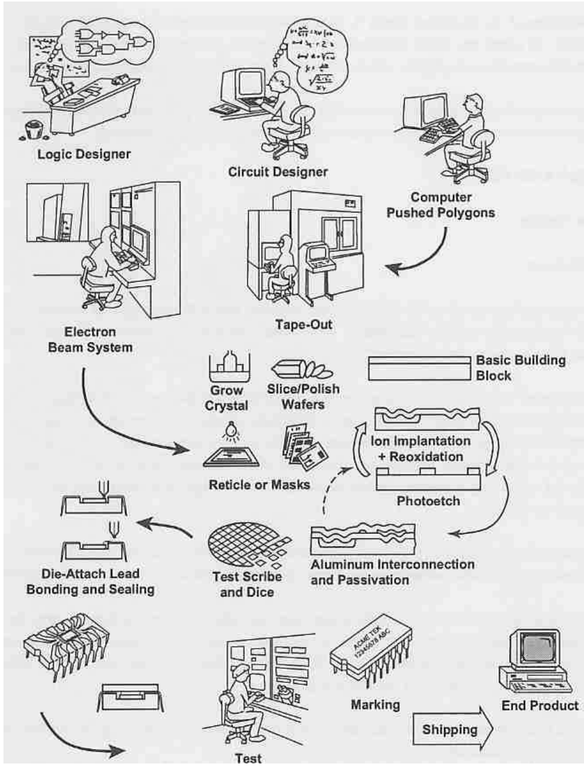

Figure 6: Semiconductor Manufacturing Process
Courtesy of Chipworks. Used with permission

The IC manufacturing process roadmap is illustrated above. The *logic designer* is either a member of the workforce of an electronic company or is a member of the design-team from the semiconductor manufacturer. The circuit designer generally works for the semiconductor manufacturer. The *circuit designer* translates the logic designer's requirements into a semiconductor design that converts the electronic plan of the circuit into the physical size of each component i.e. transistor, diode, resistor, capacitor, etc. Next, the circuit designer uses a workstation (CAD) to accomplish the design and performs the many different simulations that are required for design verification.

The geometrical layout is the final output of the workstation in the form of a *database tape*. The database tape is the input information for the electronic-beam system. The electronic-beam system uses the input data to create the masks required in semiconductor manufacturing. This is often referred to as the

"*Fab-Process*". The central region of the figure depicts the "Fab-Process" After this process is completed the wafers are sliced and tested electrically to the required specifications and than forwarded to the assembly process. The *assembly process* will package each semiconductor. After packaging is completed, the device will be given a final electronically test, and shipped to the end user.

Appendix 2: Firms in the ASIC-Industry

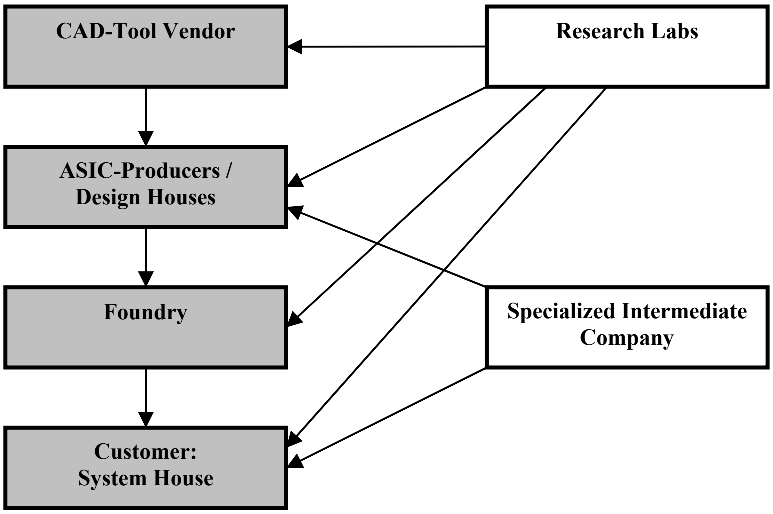

Figure 7: Firms in the ASIC-Industry.

The development and production of ASICs requires the interplay between different economic agents. The most important participants are the ASIC design houses, IC manufacturing facilities, electronic system manufacturers and CAD-tool vendors. This list can be enlarged by a number of auxiliary and/or intermediate players, such as companies offering services in the microelectronics field, firms that translate customers' needs into the specifications for the design of ASICs, and university labs. Some large system manufacturers have their own ASIC design house and foundry, they acquire or they cooperate with specialized design houses because of recurrent peaks in design work. Large electronic system manufacturers are also active on the ASIC-Market as they intend to achieve a competitive advantage for their electronic systems. These large, integrated electronic system manufacturers usually have their own fab-lines. They also make corporate-wide deals and second-source agreements with foundries. Smaller electronic companies set up agreements with different foundries and vendors to design and process their ASICs. As ASIC-designs become increasingly complex, companies establish numerous joint development and cross-licensing agreements. Given these characteristics of the industry, most strategic alliances in the ASIC-industry are likely to be strategic tools for external technology sourcing or joint development.

Appendix 3: Formal definitions of ASIC-Subfields

Table 15: Formal definitions of ASIC-Subfields.

ASIC	An application specific integrated Circuit that is designed specifically for a customer to perform only one particular function.
1. Semicustom:	**A circuit that has one or more customized mask layers, but does not have all mask layers customized, and is sold to only one customer.**
a) Gate arrays	A circuit usually composed of columns and rows of transistors, organized in blocks of gates. One or more layers are used to customize the chip.
b) Linear array	An array of transistors and resistors that performs the functions of several linear ICs and discrete devices.
2. Custom:	**A circuit that is customized on all mask layers and is sold to only one customer.**
a) Standard cell:	A circuit that is customized on all mask layers using a cell library that embodies pre-characterized circuit structures.
b) Full custom:	A circuit that is at least partially "handcrafted". Handcrafting refers to custom layout and connection work that is accomplished without the aid of standard cells.
3. PLD:	**A programmable logic device (PLD) which is a monolithic circuit with fuse, antifuse, or memory cell-based logic that may be programmed (customized), and in some cases, reprogrammed by the user.**
a) SPLD:	A Simple PLD with usually is a PAL/PLA, typically contains less than 750 logic gates.
b) CPLD:	A Complex PLD which is a hierarchical arrangement of multiple PAL-like blocks.
c) FPGA:	A Field Programmable Gate Array that offers fully flexible interconnects, fully flexible logic arrays, and requires functional placement and routing.
d) EPAC:	A Electrically Programmable Analog Circuit that allows the user to program and reprogram basic analog devices

Appendix 4: ASIC-Companies in database with descriptive statistics

Table 16: ASIC-Companies in database with descriptive statistics.

Company	Region	Included	Captive	Patents	Alliances	Avg. Sales	Avg. R&D
ABB Hafo	Europe	10 years	0	1	0	21.005,98	18,00%
Actel	USA	14 years	0	14	9	70,80	21,19%
Adams Russell Electronics	USA	3 years	0	0	0	123,91	
Advanced Linear Devices	USA	14 years	0	0	0	4,00	
Advanced Micro Devices	USA	13 years	0	13	8	1.613,84	19,19%
Agilent	USA	1 years	1	1	0	8.331,00	12,00%
Alcatel Microelectronics	Europe	14 years	1	5	5	27.137,48	11,59%
Altera	USA	14 years	0	14	8	269,55	14,63%
Analog Devices	USA	14 years	0	1	5	763,24	15,31%
Appian	USA	9 years	0	0	1	27,11	22,11%
Applied Micro Circuits Corporation	USA	14 years	0	1	3	44,65	19,51%
AT&T Microelectronics	USA	10 years	0	8	8	52.405,70	10,00%
Atmel	USA	14 years	0	11	7	441,44	15,95%
Austria Microsystems	Europe	14 years	0	0	1	86,01	14,48%
Barvon Bicmos Technology	USA	2 years	0	0	0		
BIT	USA	10 years	0	0	2	14,40	
British Airways	Europe	6 years	0	1	1	10.924,83	12,20%
California Devices	USA	14 years	0	0	1	27,23	10,79%
Calmos Systems	USA	3 years	0	0	0	2,50	
Cherry Semiconductor	USA	14 years	0	0	2	289,57	6,07%
Commodore	USA	8 years	1	0	0	867,89	2,83%
Control Data Corporation	USA	13 years	1	0	0	2.993,40	9,18%
Crossmoss	Europe	14 years	0	0	0	0,53	
Crosspoint Solution	USA	12 years	0	5	0	0,00	
CSEM IC Design	Europe	14 years	0	3	0	20,06	
Cypress	USA	14 years	0	12	7	344,41	20,02%
Daewoo	Asia	14 years	1	0	2	1.446,21	7,00%
Dialog	Europe	6 years	0	0	0	70,05	24,28%
Digital Equipment Corp	USA	8 years	1	2	3	12.043,88	11,55%

Dolphin integration	Europe	14 years	0	0	0		
Electronic Technology	USA	14 years	0	0	0	9,41	
Elron	Europe	12 years	0	4	1	30,67	20,00%
EMM	Europe	14 years	0	0	0	57,08	20,00%
Ericsson	Europe	14 years	1	3	3	11.741,71	13,82%
ES2	Europe	9 years	0	0	5	22,56	14,80%
Exar	USA	14 years	0	4	2	103,18	11,23%
Exel Microelectronics	USA	2 years	0	1	0	4,50	
Fairschild	USA	3 years	0	3	1	738,77	4,23%
Faraday Technology	Asia	8 years	0	2	0	0,00	
Faselec AG	Europe	10 years	0	0	0		
Ferranti	Europe	1 years	0	0	0	595,80	
Flextronics	USA	4 years	0	0	0	2.554,48	8,00%
Fujitsu	Asia	14 years	0	14	6	26.887,80	9,74%
Gazelle	USA	5 years	0	2	0		
GEC Plessey	Europe	12 years	0	4	5	9.621,84	7,72%
General Electric Microelectronics	USA	2 years	0	1	2	39.867,00	3,00%
General Motors	USA	11 years	1	4	3	130.122,09	7,00%
Genisis Microchip	USA	14 years	0	0	1	15,31	34,63%
Gennum	USA	14 years	0	0	1	38,11	21,36%
Gigabit Logic	USA	5 years	0	0	1	10,80	10,00%
Gould	USA	2 years	0	0	0	920,70	10,44%
Harris semiconductor	USA	13 years	0	10	5	2.981,92	16,71%
Hitachi	Asia	14 years	0	14	6	58.359,17	6,27%
HMT Microelectronics	Europe	14 years	0	0	0		
Holt	USA	14 years	0	0	0	7,74	
Honeywell	USA	14 years	0	3	1	6.652,25	5,64%
HP	USA	13 years	1	9	7	22.020,15	8,88%
Hynix	Asia	14 years	1	6	3	15.170,77	6,10%
IBM	USA	14 years	1	14	9	67.811,14	8,16%
ICT	USA	14 years	0	4	1	9,57	15,00%
Institut Microelctronica Stutgart	Europe	14 years	0	0	2		
Integrated Circuit Systems	USA	14 years	0	1	0	62,46	14,50%
Integrated Logic Systems	USA	14 years	0	1	0	1,00	47,38%
Integrated Micro Systems	Europe	14 years	0	0	0	25,60	7,66%

Intel	USA	14 years	1	13	11	11.557,29	11,48%
International Microcircuits	USA	14 years	0	0	0	16,00	15,00%
International microelectronic Pr.	USA	14 years	0	0	4	50,32	18,54%
ITT	USA	3 years	1	1	0	11.834,00	5,31%
K-Micro	Asia	14 years	1	10	2	9.848,24	1,82%
Lattice	USA	14 years	0	10	3	103,69	25,46%
LG Semicon	Asia	12 years	0	3	1	7.281,25	
Loral Federal Systems	USA	10 years	1	1	1	2.309,30	4,63%
LSI Logic	USA	14 years	0	10	10	886,29	12,33%
Lucent	USA	4 years	0	4	4	29.524,00	12,12%
M/A-Com	USA	9 years	0	0	0	410,31	5,49%
Macronix	Asia	12 years	0	1	3	239,32	9,13%
Matra Harris Semiconductors	Europe	4 years	0	0	1	3.562,65	
Matsushita	Asia	14 years	0	10	6	53.284,26	5,73%
Maxim integrated products	USA	14 years	1	2	0	203,54	14,41%
McDonnell Douglas	USA	11 years	1	0	0	14.890,27	3,30%
MCE Semiconductor	Europe	14 years	0	0	0	35,00	
Melexis	Europe	12 years	0	0	0	26,69	6,29%
Memotec AG	Europe	14 years	0	0	0		
Mentor Graphics	USA	14 years	0	2	2	374,39	18,42%
Meta design Semiconductors	USA	2 years	0	0	0		
Micro Linear Corporation	USA	14 years	0	0	0	36,60	20,64%
Micro Power Systems	USA	9 years	0	0	0	25,60	
Micro-rel	USA	14 years	1	0	0	1.762,81	10,63%
Mitel	USA	8 years	0	1	0	497,55	9,57%
Mitsubishi	Asia	14 years	0	14	6	25.508,69	4,85%
Monolithic Memories Inc	USA	1 years	0	0	0	204,80	17,24%
Motorola	USA	14 years	0	13	10	17.848,00	9,00%
National Semiconductors	USA	14 years	0	12	9	2.143,71	13,37%
NCR Micro	USA	5 years	0	3	2	5.750,64	7,07%
NEC	Asia	14 years	0	14	7	30.269,66	8,53%
Newbridge microsystems	USA	9 years	0	0	1	199,54	10,76%
Nippon Steel Corporation	Asia	12 years	0	1	3	24.042,52	16,90%
Nordic VLSI	Europe	14 years	0	0	1	10,65	
Northop Grumman	USA	3 years	1	1	1		

Oki Electric	Asia	14 years	0	7	3	5.049,30	5,17%
Orbit Semiconductors	USA	10 years	0	0	0	27,50	9,35%
Panatech Semiconductor	USA	1 years	0	0	0	9,79	2,45%
Philips	Europe	14 years	0	11	10	32.398,67	7,02%
Plessey Semiconductor	Europe	2 years	0	0	2	2.277,35	6,09%
Plus Logic	USA	5 years	0	3	0		
PLX	USA	14 years	0	1	0	17,93	20,74%
Polycore Electronics	USA	2 years	0	0	0		
Prema	Europe	14 years	0	0	0	13,00	
Quicklogic	USA	13 years	0	11	6	20,64	21,55%
Raytheon	USA	12 years	0	2	2	9.700,75	3,04%
Ricoh	USA	14 years	0	7	0	8.115,38	5,59%
Rockwell	USA	12 years	1	3	3	11.418,58	8,48%
Rohm	Asia	14 years	0	5	3	1.740,20	3,23%
Rood Technology	Europe	14 years	0	0	0	48,79	
S3	Europe	14 years	0	0	2		
Samsung	Asia	14 years	0	6	7	12.255,45	3,07%
Sanyo	Asia	14 years	0	5	5	12.768,33	5,08%
Schlumberger	USA	1 years	1	1	1	4.568,40	8,47%
Seattle Silicon	USA	13 years	0	0	0	7,00	
Seiko Epson	Asia	14 years	0	9	4	5.123,66	9,77%
Sharp	Asia	14 years	0	2	5	12.191,17	6,38%
Siemens	Europe	14 years	0	11	7	49.375,06	9,68%
Sierra PMC	USA	14 years	0	2	1	98,93	24,43%
Silicon Compiler Systems	USA	4 years	0	0	0	22,50	
Silicon Systems	USA	2 years	0	0	0	83,50	10,79%
Siliconix	USA	4 years	0	0	0	121,18	14,53%
Sipex	USA	14 years	0	1	0	37,35	9,72%
SIS Microelectronics	Asia	12 years	0	0	0	1,48	
Sony	Asia	14 years	0	7	5	32.791,28	6,22%
Spraque Solid State	USA	4 years	0	0	0	472,50	3,82%
ST Microelectronica	Europe	14 years	0	13	11	2.436,79	15,88%
Standard Microsystems	USA	14 years	0	0	6	205,34	13,11%
Supertex	USA	14 years	0	0	0	29,73	13,32%
Swindon Silicon Systems	Europe	14 years	0	0	0		

TDK	Asia	8 years	0	0	0	4.108,27	8,00%
Tektronix	USA	8 years	0	0	1	1.361,34	13,59%
Temic	Europe	12 years	1	0	6	56.580,21	13,37%
Thesys Microelectronics	Europe	9 years	0	0	3	20,00	15,00%
Thomson CSF Semiconducteurs	Europe	13 years	1	2	6	6.356,65	10,84%
TI	USA	14 years	0	13	10	7.907,71	9,21%
TLSI	USA	14 years	0	0	0	572,40	0,80%
Toshiba	Asia	14 years	0	14	9	37.045,59	6,22%
Triquent	USA	9 years	0	1	1	63,16	21,56%
Tyco	USA	5 years	1	1	1	10.404,10	6,00%
Unicorn	Asia	14 years	0	2	3	433,71	8,57%
Universal	USA	14 years	0	0	0	14,08	16,00%
UTMC	USA	13 years	1	6	1	20.961,15	5,10%
Vertex	USA	6 years	0	0	1	1,00	40,00%
Vitesse	USA	14 years	0	1	4	58,45	31,47%
VLSI Semiconductor	USA	13 years	0	10	12	443,15	16,20%
VTC	USA	11 years	0	0	0	103,00	15,00%
Wafer Scale Integration	USA	14 years	0	5	4	30,33	15,00%
Western Digital Corporation	USA	9 years	1	0	1	922,37	8,39%
Westinghouse	USA	10 years	1	4	1	10.622,10	7,51%
Xerox	USA	14 years	1	2	1	16.427,36	5,42%
Xilinx	USA	14 years	0	14	5	252,94	13,33%
Yamaha	Asia	14 years	1	2	1	4.211,59	
Zentrum Mikroelectronik Dresden	Europe	14 years	0	0	1	21,92	
Total (158 firms)	*usa(99)*	*1723 years*	*29*	*506*	*381*		
Average	*eur (35)*	*10,91*		*3,20*	*2,41*	*8.102,77*	*12,08%*
Standard Deviation	*asia(24)*	*4,29*		*4,53*	*3,05*	*16.860,51*	*7,52%*

Appendix 5: Distribution of alliances by type

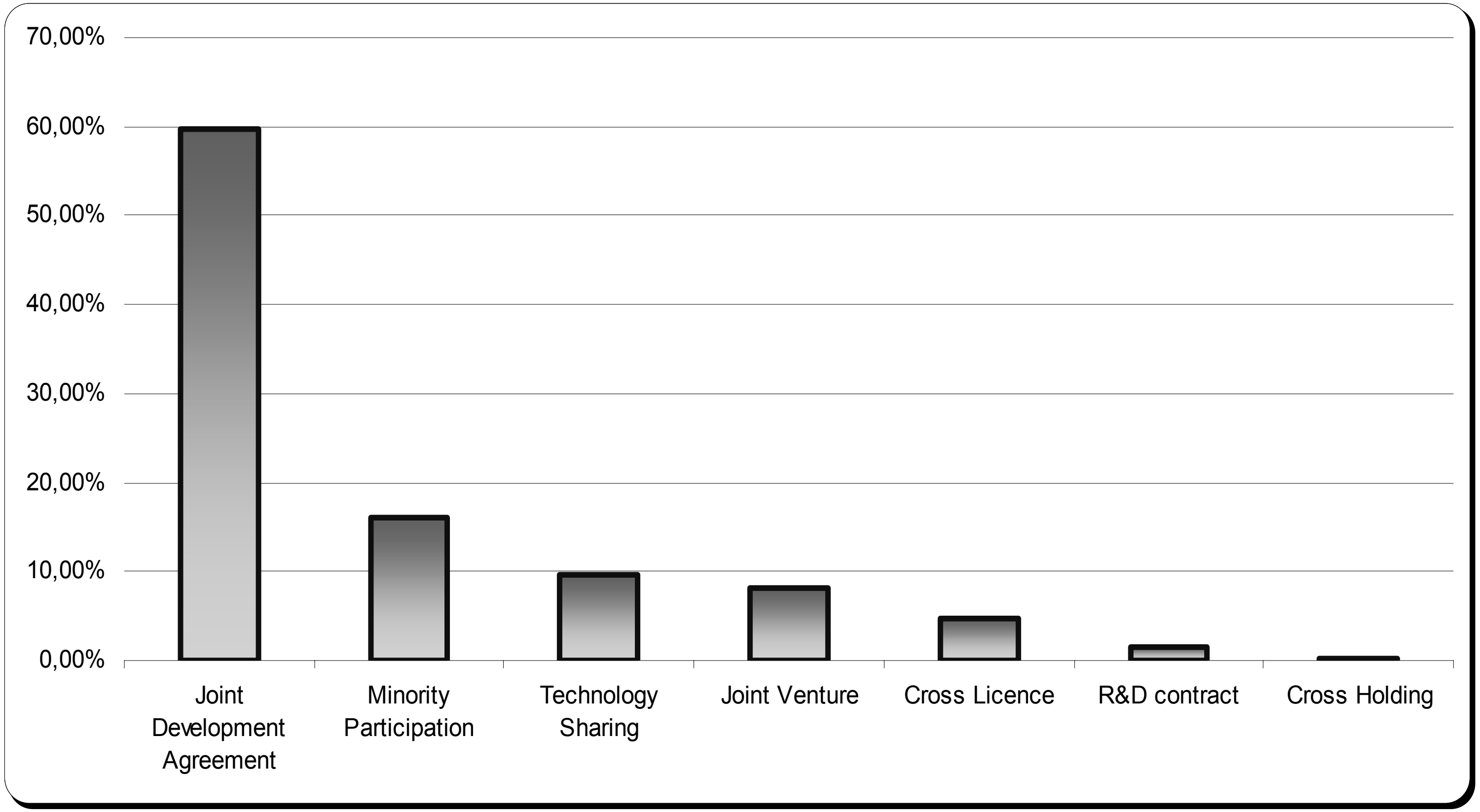

Figure 8: Distribution of alliances by type.

Appendix 6: Descriptive statistics alliance network 1984-2000

Table 17: Descriptive statistics alliance network 1984-2000.

	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
New alliances $_{(t)}$	42	40	46	43	30	24	19	35	37	20	39	43	35	44	59	46	47
Clique Sp. Ties $_{(t)}$	3	7	3	7	5	6	3	13	8	4	9	10	5	5	12	3	3
Av. tie per firm $_{(t1-5)}$	1.88	1.96	2.13	2.10	2.25	2.24	2.23	2.19	2.44	2.55	2.51	2.57	2.57	2.26	2.12	2.29	2.12
Nr. of cliques $_{(t1-5)}$	7	16	21	27	30	27	26	28	35	33	33	34	42	41	35	39	34
Av. clique size $_{(t1-5)}$	5.72	6.13	7.33	6.85	8.00	7.41	6.96	6.71	7.11	7.61	7.18	7.26	7.31	6.83	6.51	7.43	8.44
Percent in clique $_{(t1-5)}$	0.37	0.41	0.47	0.54	0.64	0.71	0.72	0.70	0.78	0.75	0.73	0.73	0.73	0.68	0.63	0.64	0.54
Cl. coefficient $_{(t1-5)}$	5.37	4.20	4.63	4.86	4.15	4.19	4.49	4.49	4.16	4.21	4.24	4.31	4.14	4.48	5.01	4.70	4.43
Path Length $_{(t1-5)}$	0.27	0.31	0.29	0.23	0.23	0.20	0.17	0.18	0.12	0.14	0.15	0.13	0.18	0.13	0.09	0.12	0.16
Small World $_{(t1-5)}$	3.05	5.45	6.00	7.21	9.68	8.84	7.94	7.92	5.45	5.49	5.27	5.19	7.93	6.25	5.02	7.68	10.05

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Summary (in Dutch)

Bedrijven zijn de laatste decennia in toenemende mate afhankelijk geworden van kennis en technologieën die alleen buiten de eigen organisatie beschikbaar zijn. Om toegang tot deze kennis en technologieën te verkrijgen zijn bedrijven vaker en intensiever gaan samenwerken met een breed assortiment aan strategische partners. Met name in high-tech sectoren is samenwerking essentieel om innovatieve technologieën te ontwikkelen en op de markt te brengen. Binnen deze sectoren is een levendig netwerk ontstaan waarin bedrijven onderling kennis en technologie uitwisselen.

Wetenschappers hebben frequent waargenomen dat binnen deze netwerken groepen bedrijven ontstaan die veelvuldig met elkaar samenwerken, zogenaamde cliques. Dit proefschrift richt zich op deze cliques en heeft daarbij bekeken of situering binnen deze cliques bijdraagt aan de innovatiekracht van bedrijven. Bedrijven kunnen profiteren van een situering binnen cliques doordat er meer kennis en technologieën beschikbaar zijn en doordat deze kennis en technologieën efficiënter overgedragen worden. Dit proefschrift toont empirisch aan dat situering binnen cliques bijdraagt aan de innovatiekracht van bedrijven. Dit proefschrift toont echter ook aan dat niet alle bedrijven weten te profiteren van situering binnen deze cliques.

Bedrijven die een centrale positie innemen binnen de clique en bedrijven die samenwerkingsverbanden onderhouden met bedrijven in andere cliques, zijn significant innovatiever dan bedrijven zonder deze kenmerken. Deze samenwerkingsverbanden met bedrijven in andere cliques zijn vooral van belang gedurende perioden van technologische verandering. Een mogelijke verklaring hiervoor is dat de kennis en technologie van bedrijven binnen de eigen clique meer overlap heeft met de eigen kennis en technologie dan de beschikbare kennis en technologie van bedrijven in andere cliques.

Daarnaast is gekeken naar factoren die kunnen verklaren waarom bepaalde bedrijven succesvol zijn in het aangaan van samenwerkingsverbanden met bedrijven in andere cliques. De resultaten van dit proefschrift tonen aan dat bedrijven die minder intens betrokken zijn in de clique, ervaring hebben met samenwerkingsverbanden en de beschikking hebben over recente technologieën, beter in staat zijn deze samenwerkingsverbanden aan te gaan.

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Michiel Pieters was born on august 18, 1977 in Alkmaar, the Netherlands. He attended the Lorentz-Casimir Lyceum in Eindhoven, where he graduated in 1996. In the same year, he started his study Sports Economics at the Fontys Hogeschool in Tilburg. In 2000 he started his study Policy and Organisation Sciences at the University of Tilburg where he graduated in 2003. After his graduation he started his PhD research in May 2004 at Hasselt University, Belgium. Next to his research he taught Business Strategy for 3 consecutive years. During his research he was a guest researcher at Eindhoven University of technology at the sub-department Innovation, Technology, Entrepreneurship and Marketing.

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