![Ecis logo](Ecis — Eindhoven Centre for Innovation Studies)

Technological capability building through networking strategies within high-tech industries

Wim Vanhaverbeke, Geert Duysters and Bonnie Beerkens

Eindhoven Centre for Innovation Studies, The Netherlands

Department of Technology Management

Technische Universiteit Eindhoven, The Netherlands

December 2001

Technological capability building through networking strategies within high-tech industries

Wim Vanhaverbeke, Geert Duysters and Bonnie Beerkens

Wim Vanhaverbeke
Eindhoven University of Technology
e-mail: w.p.m.vanhaverbeke@tm.tue.nl

Geert Duysters
Eindhoven University of Technology
e-mail: g.m.duysters@tm.tue.nl

Bonnie Beerkens
Eindhoven University of Technology
e-mail: b.e.beerkens@tm.tue.nl

Direct correspondence to:
Wim Vanhaverbeke
Eindhoven Centre of Innovation Studies
Eindhoven University of Technology
P.O. Box 513
5600 MB Eindhoven
The Netherlands

September 2001

Technological capability building through networking strategies within high-tech industries

Abstract

Learning through networks has been a research topic for several years now. Technological learning is more and more based on a combination of internal and external learning and firms need to develop both technological and social capital for that purpose. This paper analyses the relationship between both types of capital and their impact on the technological performance of companies in high-tech industries. We claim and find strong empirical evidence that technological capital and social capital mutually reinforce each other's effect on the rate of innovation for companies with small patent and alliance portfolios. However, when companies have a strong patent portfolio and an extensive network of alliances then both types of capital become substitutes. We also found that there are two possible equilibriums: the first one emphasizes the development of strong internal technological capabilities supported by a small alliance portfolio. The second is the mirror image of the first one: these firms focus mainly on technology acquisition through alliance partners supported by a minimum of internal technological capabilities. Both strategies can co-exist in an industry. Finally, we find empirical evidence that companies who explore novel and pioneering technologies have a higher rate of innovation in subsequent years.

INTRODUCTION

This study aims to relate technological performance of companies in high-tech industries to their degree of technological and social capital. More specifically, we focus on three main research topics. First, we consider whether a firm's technological and social capital are mutually enforcing factors that together determine the rate of innovation, or whether they can be considered as substitutes. We also address the question of whether there is an optimal mix of resources, which produces above average results. Second, following Stuart (2000) we argue that not so much the size of the alliance portfolio, but the technological performance of the partnering firms to whom a focal firm is connected determines the rate of innovation of the latter. Finally, we aim to find out whether companies that explore new technologies have higher rates of innovation than companies that are primarily engaged in exploiting and strengthening their existing technology base.

The apparent importance of knowledge, especially in high tech industries, has given rise to a stream of research focusing on knowledge as the single most important resource within an organisation (Kogut and Zander, 1992; Conner and Prahalad, 1996) and has led to the emergence of the knowledge based theory of the firm (Grant 1997). In a similar vein, a number of recent studies have investigated the relationship between a portfolio of technology alliances and (technological) firm performance (Hagedoorn and Schakenraad, 1994; Shan, Walker and Kogut, 1994; Powell, Koput and Smith-Doerr, 1996; Mitchell and Singh 1996; Stuart, 2000). Firms are increasingly forced to combine internal technological strengths with those of other firms as R&D costs soar rapidly and technological dynamics speed up. Products require more and more sophisticated technologies and emerging technologies have the potential to undermine the competitive positions of incumbents. Many of these alliances are 'learning alliances' through which companies can speed up their capability development and exploit knowledge developed by others (Grant and Baden-Fuller, 1995). Because in today's turbulent technological environment no single firm is able to come up with all the required technological capabilities themselves, firms are increasingly induced to form these 'learning alliances'. In order to overcome the lack of specific technological capabilities they try to tap into other companies' technological assets. Market transactions are generally considered to be

only a weak alternative to alliances because most valuable knowledge is cumulative and tacit in nature. This specific nature makes it hard to transfer between organizations through market transactions (Mowery, 1988; Mowery *et al.*, 1995; Osborn and Baughn, 1990).

Technological learning is more and more based on a combination of internal and external learning: internal learning by the internal development of new products and processes as a result of internal R&D, external learning from the technology acquired through technology alliances. Both types of learning are considered complements reinforcing each other's productivity (Cohen and Levinthal, 1990; Duysters and Hagedoorn, 2000). Moreover, companies can only tap into other companies' technology base successfully if they have sufficient absorptive capacity (Lane and Lubatkin, 1998). In its turn, absorptive capacity results from investments in internal technological know-how. Hence, internal technological knowledge and external technology acquisition via alliances are considered complements. But surprisingly, there are to our knowledge no large-sample empirical studies that focus on the combined effect of internal and (quasi) external knowledge acquisition on the technological innovative performance[1].

THEORETICAL BACKGROUND AND HYPOTHESES

Technological and social capital

This paper builds on the knowledge-based view of the firm. Over time accumulated knowledge assets constitute the source of a firm's sustainable competitive advantage in the marketplace (Kogut and Zander, 1996; Spender, 1996). Firm specific knowledge assets are of strategic interest – they are distinctive competences - because they are rare, imperfectly tradable and hard to imitate and must be build within the organization internally as long as part of the technological know-how is not

---

[1]   Ahuja (2000) focuses on the impact of technical, commercial and social capital of companies on the formation of new alliances. Commercial resources are those required to convert technical innovations to products and services. They consist of manufacturing and marketing capabilities and entail manufacturing facilities and service and distribution networks (Mitchell, 1989; Teece,

articulated or tacit in nature. The development of knowledge assets (or technological capital) is difficult, time consuming and expensive. Moreover, developing technological capabilities is a risky venture because R&D up-front costs may be huge and the technological and commercial outcomes may be highly uncertain (Mitchell and Singh, 1992).

Because of the cumulative character of technology, the current technological position of a company is shaped by the path it has traveled (Teece, Pisano and Shuen, 1997). Hence, path dependency is crucial: previous investments in and strategic choices about technology development not only explain the current position of a company, but they also constrain the future options of companies. Therefore, companies that failed to build up a technological capability in the past may find it difficult to catch up later by internal development (Shan, 1990). Furthermore, existing technological capabilities may reduce a firm's capacity to adapt to new commercial challenges or to rejuvenate its capabilities in the face of new, 'competence destroying' technologies (Abernathy and Clark, 1985).

Accumulated technological competence can therefore be seen as the result of past innovative activities of a firm (Podolny and Stuart, 1995; Stuart *et al.*, 1999). As a result, we can expect that firms with well developed technological assets will be more innovative than other firms under conditions of relative technological stability – i.e. when companies can build on their previously developed knowledge. This argument suggests the following hypothesis.

Hypothesis 1: *The greater the technological capabilities of a firm at t-1 the higher its rate of innovation at t*

Being centrally positioned in a network of technology alliances has been recognized as a distinctive and important form of capital – social capital - of innovative companies (Gulati, 1995, 1999). Especially in fast changing technological fields internal R&D efforts need to be complemented by external means of technology acquisition. The creation of a strategic alliance network can facilitate the access to

---

1986). In what follows we focus on the relationship between technical and social capital and neglect the linkages with commercial capital.

4

technological resources across industries or technological field. Alliances are often used by companies as instruments to acquire technological knowledge and to develop new skills that reside within the partnering companies (Hamel, 1991; Hagedoorn and Schakenraad, 1994; Powell *et al.,* 1996). Previous research established that alliances often have a positive impact on the performance of companies (Baum and Oliver, 1991; Mitchell and Singh, 1996; Uzzi, 1996; Powell et al., 1996; Hagedoorn and Schakenraad, 1994). These authors found in different research settings a positive relationship between technological alliances and rates of innovation. A notable exception is the work of Stuart (2000) who found no significant relationship between the number of alliances and the growth rate or rate of innovation of semiconductor firms.

A portfolio with too many alliances may lead to saturation and overembeddedness (Kogut *et al.*, 1992; Uzzi, 1997). Therefore, at high levels of embeddedness marginal benefits of forming new linkages will be low and marginal costs of additional links will be relatively high (Ahuja 2000). Nahapiet and Ghoshal (1998, p. 245) argue that the collective social capital resulting from dense networks can limit a firm's "openness to information and to alternative ways of doing things, producing forms of collective blindness that sometimes have disastrous effects". At the same time managerial costs increase significantly because not only individual alliances need management attention, but management also has to coordinate across linkages (Harrigan, 1985). Gomes-Casseres (1996) has shown that there is a natural limit to the number of alliances that a company can manage successfully. Therefore, we argue that there is a non-linear relationship between the social capital of a company and its rate of innovation. Highly embedded companies or firms with poorly developed social capital will have the lowest rates of innovation. In particular firms at intermediate levels of embeddedness will show the highest rates of innovation. This argument suggest the following hypothesis:

Hypothesis 2: *The involvement of a company in technology-based alliances at t-1 is related in a curvilinear way (inverted-U shaped) to its rate of innovation at t*

As discussed above, technological learning is increasingly based on a combination of internal and external learning. Both types of learning have been described in the

literature as complements reinforcing each other's productivity (Cohen and Levinthal, 1990; Duysters and Hagedoorn, 2000).

Whether social and technological capital would have mutually reinforcing effects under all circumstances is however open for debate. Firms with low degrees of technological competences and social capital, in terms of the number of alliances they have, will benefit considerably from entering new alliances since they provide access to new and valuable technological knowledge. Firms with poorly developed technological capital have strong incentives to get access to the technological capital of other firms through interorganizational alliances (Mitchell and Singh, 1996). These companies will also profit from strengthening the internal knowledge base as this increases their absorptive capacity so that its partners' knowledge can better be valued and assimilated (Lane and Lubatkin, 1998).

Firms with unique internal knowledge resources are likely to be attractive to other firms that expect to benefit from getting access to these resources through means of alliances (Baum *et al.* 2000). As a result, firms with unique technological resources have more opportunities to collaborate than firms with poorly developed resources. However, firms that are already well endowed with technological capital have fewer incentives to cooperate in order to improve their own rate of innovation (Ahuja, 2000). Because these companies have already developed leading edge technological competences they are likely to learn to a lesser extent from their partners than vice versa (Hamel, Doz and Prahalad, 1989; Kale, Singh and Perlmutter, 1999; Khanna, Gulati and Nohria, 1998).

As a result, a company that is well endowed with technological competences is likely to benefit only marginally from extending its alliance network beyond a critical threshold because it increases the chance that internally developed and externally acquired technology may overlap or that the marginal value of getting access to another company's knowledge base is smaller than the cost to set up and manage the alliance (Harrigan, 1985). Hence, although it is very unlikely that companies can develop their technological resources completely in-house those that have unique technological resources need only a relatively small alliance network to ensure high rates of innovation. Beyond a critical threshold both types of capital substitute each

other and extending social capital may become a liability. This argument suggests the following hypothesis:

Hypothesis 3:   *At low levels, internal technological capabilities (technological capital) and external acquisition of technology through technological alliances (social capital) reinforce each other's effect on the rate of innovation. At high levels, they weaken each other's effect.*

Combining hypotheses 2 and 3, we expect that companies can realize the highest rates of innovation by two different types of strategies that can coexist in the same industry. The first strategy is based on a considerable alliance network and a small (potentially specialized) technological capital. This provides the company with ample opportunities to tap into its partners' technology resources or to co-develop innovations by combining (complementary) skills. The second strategy emphasizes the internal development of innovations in the company. The company has an extensive patent portfolio and needs only a few alliances to ensure that it has the required technology to strengthen or to continue its strong technological performance. Companies with moderate values for both types of capital, failing to stick to one of these two strategies, are 'stuck in the middle'. Thus:

Hypothesis 4:   *Companies with extensive (small) internal technological capabilities and a small (extensive) alliance network have the highest rates of innovation. Both profiles may successfully coexist in an industry.*

Stuart (2000) argues that the technological (and economic) performance of companies is not so much determined by the size of the alliance network but rather by the characteristics of the focal company's alliance partners[2]. If companies enter alliances to get access to other firms' technology, then those with a large stock of technological resources are highly attractive as potential alliance partners. Stuart finds evidence that alliances with partners that are technologically well endowed have a larger positive impact on post-alliance performance of the focal firm. In high-tech industries the technological competencies of alliance partners determine in part the focal company's potential to learn. Teaming up with skilled innovative companies with unique

---

[2]   Similarly, Baum, Calabrese and Silverman (2000) argue that the performance of biotechnology start-ups is positively influenced by the technological capabilities of the partnering companies.

technological assets offers a company the best opportunities to learn and thus to invigorate its competitive position.

Hypothesis 5:   *The stronger the technological capabilities of a company's alliance partners at t-1, the higher its rate of innovation at t.*

Exploring new technologies

We have already argued that a mutual positive feedback between experience and competence exists. This virtuous cycle enables companies to build up unique technological skills, which potentially lead to competitive advantages in the marketplace. The increased ease of learning within particular technologies facilitates the exploitation of these technologies compared to the exploration of new technologies (Levinthal and March 1993; March, 1991).

The downside of this path dependency is that it increases the likelihood of a company falling in the so-called familiarity trap (Ahuja and Lampert, 2001). It is argued that experience and competence in a specific set of technologies lead to the emergence of a dominant and increasingly rigid technological paradigm. This, in turn, reduces the probability of a company's willingness to experiment with other problem solving approaches. This absence of experimentation reduces the chance that a company will discover new technological opportunities that are assumed to be large in high tech industries (Jaffe, 1986; Lunn and Martin, 1986; Levin *et al.*, 1985).

To avoid familiarity traps companies can explore *novel technologies* - i.e. technologies that are new to the organization even though they may have been in existence earlier (Ahuja and Lampert, 2001). Experimenting with novel technologies allows a company to value the potential of these technologies in a more accurate way (Cohen and Levinthal, 1990). Explorative companies are better positioned to discover the technological and commercial potentials of novel technologies. They may also be better prepared to value the potential competitive threat of disruptive technologies (Bower and Christensen, 1995; Christensen and Overdorf, 2001) or competence destroying technologies early on (Abernathy and Clark, 1985; Tushman and Anderson, 1986). Exploring novel technologies challenges the dominant problem-

solving paradigm in companies (Lei *et al.*, 1996). Unfamiliar technologies may force a firm to search for new cognitive maps that open up new avenues for research. Hence, we may expect that companies that experiment with novel technologies are better positioned to have a higher rate of innovation than firms that invest all their efforts in exploiting existing, familiar technologies.

Exploring novel technologies, however, is only advantageous up to a point. Investing excessively in exploration of novel technologies may lead to confusion: exploration of unfamiliar technologies and exploitation of familiar ones have to be balanced to be productive. As argued by March (1991) and Levinthal and March (1993) firms engaging in exploration exclusively, only suffer from the costs associated with experimentation without exploiting its benefits. Moreover, there will always be a trade-off between investing in deepening and upgrading the existing technologies to safeguard profits today and exploring new technologies to secure future profits (Rowley *et al.*, 2000; Levinthal and March, 1981). Finally, scattering R&D resources on many novel technologies may eventually lead to diseconomies of scale within the individual technologies (Ahuja and Lampert, 2001). Therefore, we argue that:

Hypothesis 6: *A firm's rate of innovation at t is related in a curvilinear way (inverted-U shaped) to its exploration of novel technologies at t-1.*

Innovative firms generally search for technological solutions within the scope of what has been invented before. They tend to build on their own technological successes and on those of others[3]. Previous solutions offer technologists or scientists an anchor to move forward. As a result, building on technological antecedents is less risky than working on a *de novo* innovation (Hoskisson, Hitt and Hill, 1993; Hoskisson, Hitt and Ireland, 1994).

Ahuja and Lampert (2001) refer to the tendency of firms to search near to old solutions as the *propinquity* or nearness trap. Often interesting technological fields remain unexplored when companies rely too much on old solutions. The literature however suggests that important inventions emerge, in particular, from these unexplored areas (Utterback, 1994). Experimenting with *pioneering* technologies –

---

[3] An average of 18 patent citations for the 1850 patents in the sample of ASIC related patents.

i.e. technologies that do not build on existing technologies (Ahuja and Lampert, 2001) - is one possible way to circumvent the dangers of the propinquity trap. Experimenting with pioneering technologies is an attempt to jump to different technological trajectories (Dosi, 1988, Foster, 1986; Sahal, 1985). Since pioneering technologies offer fundamentally new solutions they may generate large future profit streams for the innovative company. At the same time, they entail large risks typical for radical innovations: However, when a company increases the number of experiments it also inflates the probability that a major, successful innovation will pop up sooner or later. We expect that a company having successfully patented a 'pioneering technology'-innovation will increase its rate of innovation in the subsequent years.

Hypothesis 7: *A firm's rate of innovation at t is positively related to its success in pioneering new technologies at t-1.*

EMPIRICAL SETTING

Definition and characteristics

The hypotheses were tested on the population of ASIC-producers that were active in the period 1988-1996. ASICs - i.e. application-specific integrated circuits - are a special type of ICs (integrated circuits) accounting for about 12 % of worldwide IC sales in 1995. The term 'ASIC', as now in use in the industry, is a misnomer. In reality these ICs are customer-specific rather than application-specific since an ASIC is a device made for a specific customer[4].

The ASIC market is a typical high-tech industry where technology is the driving force shaping competition among firms. R&D-to-sales ratios are exceptionally high. The ASIC market can be divided into different submarkets. According to the "Integrated Circuit Engineering Corporation" (ICE) the ASIC market includes the following

---

[4]   A device which is made for one particular type of system function (e.g. disk-drives, CD-players, video compressing) but is sold to more than one customer, is called an ASSP (application-specific standard product, sometimes also called ASIPs - application-specific integrated processors). Although ASSPs are manufactured using ASIC technology, they are ultimately sold as standard devices to large numbers of users.

categories of ICs: arrays, custom ICs, and programmable logic devices (PLDs). Formal definitions are given in Table 1 and diagrammed in Figure 1.

Insert Table 1 about here
Insert Figure 1 about here

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 houses 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. The interplay between different agents is shown in Figure 3.

Insert Figure 3 here

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. In a turbulent high-tech environment like the ASIC-industry, firms are likely to link up with each other in order to keep up with the newest technologies (Duysters and Hagedoorn, 1996).

DATA, VARIABLES AND MODELING

Data

Three types of data are combined in this paper. The cumulated technology alliances between the different players in the ASIC technology field capture social capital. Technological capital is measured by means of the cumulated US patents of each company. Finally, a set of financial data is gathered for each ASIC producer.

The data on strategic alliances were selected from the MERIT-CATI databank on strategic technology alliances (Duysters and Hagedoorn 1993)[5]. The selection included strategic alliances (SAs) which major focus was on (technological developments in) the ASIC-industry. The MERIT-CATI databank covers the period between 1975 and 1996: For that period 288 ASIC related strategic technology alliances were detected. There were 130 different firms involved in these SAs.

Insert Figure 4 about here

A sharp increase in SAs occurred in the early and mid-eighties. Their popularity diminished in the late eighties and the early nineties. SAs in the ASIC industry are mainly non-equity agreements (79.2%) of which the majority is joint development agreements (56.9% of all SAs). Joint ventures, which account for 12.8% in the ASIC industry are the most important form of equity SAs. The distribution of different types of SAs is presented in Figure 5.

Insert figure 5 about here

To measure technological capital, we used patent data from the U.S. Patents Database for all companies involved in the design and production of ASICs, also those based outside the US[6]. Working with U.S. patents – the large patent market - is preferable to the use of several national patent systems. Nations differ in their application of standards, systems to grant patents and value of the protection granted (Basberg, 1987; Griliches, 1990). Especially in industries where companies operate on a global scale, such as the ASIC-industry, U.S. patents may be a good proxy for companies' worldwide innovative performance[7].

---

[5]   Strategic technology alliances include joint research projects, joint development agreements, cross licensing, (mutual) second source agreements, technology sharing, R&D consortia, minority holdings and joint ventures, but no licensing agreements or production and marketing agreements.

[6]   The patents were selected by means of a query on 'ASIC' and related concepts/definitions such as 'gate array', 'linear array', 'FPGA', 'PLD', 'full custom', 'SPGA' and 'EPAC'.

[7]   Patents can be categorized by means of the International Patent Classification, an internationally recognized hierarchical classification system comprising 118 broad sections and 624 subclasses nested within the classes. It is furthermore possible to subdivide the subclasses into 67.000 groups. ASIC-related patents are classified in a relatively small set of subclasses (75 in total).

Financial data of ASIC producers have been gathered from different sources among which the annual ICE reports (McClean, 1985-1998). The data contain the ASIC-sales of these companies, their total IC-sales, the distribution of the ASIC-sales across the three segments, R&D-intensity on the corporate level and total sales. We furthermore included the nationality of each company.

Variable definitions and operationalization

To test the hypotheses we constructed a number of variables. Table 2 summarizes them.

Insert here table 2

Dependent variable

Explaining the technological learning capacity of different ASIC producers requires an operationalization of the change in size of a company's technological capital. Changes in technological capital are operationalized by patents granted to an innovating company. However, the patent is recorded in the database at the time the company applied for the patent (rather than the year when it was granted to the firm) because a patent application is a signal that a company has successfully developed a technological innovation. The dependent variable is a count variable measured by the number of patents that a company applied for in a particular year[8].

Independent variables

The first 5 hypotheses suggest a relationship between a firm's prior technological capital past, its social capital and the technological characteristics of its alliance partners on the one hand and its ex post technological performance on the other hand.

---

[8]   Of course, we only keep track of patents that have been granted by the U.S. Patent Office before the end of 2000. The observation period is 1988-1996. We do not expect to have a significant bias at the end of that period, because most patents are granted within a period of 2 to 3 years (average time for all patents in the sample is 26 months). Of the 1381 patents that were filed between 1/1/1988 and 31/12/1996 only 50 (or 3.6%) were granted after 4 years.

Cumulative technological capital is calculated as the number of ASIC-related patents that an ASIC-producer obtained in the previous 4 years. Patents granted to a company are used to measure, in an indirect way, the technological competence of a company (Narin, Noma and Perry, 1987). A moving window of 4 to 5 years is the appropriate time frame for assessing the technological impact in high-tech industries (Podolny and Stuart, 1995; Stuart and Podolny, 1996; Henderson and Cockburn, 1996; Ahuja, 2000). Studies about R&D depreciation (Griliches, 1979, 1984) suggests that knowledge capital depreciates sharply, losing most of its economic value within 5 years. As a result, a 4 or 5-year period is appropriate to assess technological relevance. In this paper we use the cumulated patents obtained by a firm during the last 4 years as a measure for the technological competence of an ASIC producer. Variables using a 3 and 5-year time window were also calculated to check for the sensitivity of this variable to the length of the time period. These variables are highly correlated with the 4-year time window (r = 0.94 for the 3 year window and 0.96 for the 5 year window), suggesting that the measurement of technological capital is not sensitive to the choice of a particular time window.

Following Gulati (1995), we computed social capital from matrices including all alliance activities of the ASIC-producers prior to a given year. In constructing measures of social capital based on past alliances, a number of choices have been made. First, we do not consider different types of alliances separately[9]. Second, some authors weigh each type of SA according to the 'strength' of their relationship (see Contractor and Lorange, 1988; Gulati 1995; Nohria and Garcia-Pont 1991). As some technology alliances are more important than others in creating and transferring technological know-how we followed this weighting procedure to construct the social capital variable[10]. The third choice relates to the length of the period during which the existing alliance portfolio is likely to have an influence on the current technological performance of a company. All

---

[9] Figure 5 gives an overview of the different alliance types: alliances vary from equity joint-ventures and minority holdings with a strong organizational commitment and interdependence between allies to non-equity alliances which imply only moderate levels of organizational commitment (although stronger than arms' length licensing agreements).

[10]

Type	Weight	Type	Weight
Cross licensing	1	R&D contract	4
Technology sharing	2	Joint development agreement	4
(Mutual) second source agreement	3	Minority holding	5
State intervention R&D	3	Joint venture	6
Research corporation	3		

past alliances can be included into the calculation of social capital assuming that all prior ties, no matter how long ago they were established, have an impact on current firm behavior. However, we chose for a moving window approach, assuming that only 'ongoing' alliances have an impact on the technological performance of the focal firm. For the alliance activities of the ASIC producers we have an indication about the termination of 62 (21.5%) alliances in the observation period 1988-1996. We assumed they have an impact on the rate of innovation as long as they were not terminated. For the other alliances we assume that the lifespan of alliances is usually no more than five years (Kogut 1988, 1989).

The innovative performance of a company's partners can be modeled in different ways. Basically, we follow the method developed by Stuart (2000). The innovative performance of a firm i at time t is denoted as d_{it}. For each year in the observation period 1988-1996, an Nx1 vector $\mathbf{d_t}$ represents the innovation scores of the N firms in the sample. Combining these innovation scores with alliance activity in the ASIC-industry allows the construction of compact, time-varying innovation measures of the alliance partners of each company. These measures are computed by creating first a NxN (firm-by-firm) time changing symmetrical alliance matrices, labeled $\mathbf{W_t}=[w_{ijt}]$.

The innovative performance of the alliance partners of each ASIC-producer at time t ($\mathbf{p_t}$) is the product of the alliance matrix with the corresponding vector of innovative performance scores. As a result $\mathbf{p_t}$ is a time-changing vector containing the summed innovative performance scores for the allies of each ASIC producer.

The innovative performance of the partners can be measured in different ways. One possible way is to count the patents received by each of the companies during the previous 4 or 5 years (Stuart and Podolny, 1996; Ahuja, 2000; Baum, Calabrese and Silverman, 2000). An alternative is to weight these patents by the number of times they have been cited by more recent patents. Patent citation counts are important indicators of the technological importance of an innovation (Albert *et al.*, 1991; Narin, Noma and Perry, 1987). A small inconvenience of patent citations is that the patents applied for in the last years of the observation period 1988-1996 have a shorter 'citation-period' than those that have been filed for in the beginning of that period. The majority of citations appear in the first five years after the patent was granted: as

a result, although we cannot exclude a potential bias we expect that this will not have a major impact on the results.

Novel technologies measure the degree to which a company experiments with technologies that were not used previously (Ahuja and Lampert, 2001). To construct this variable we used the International Patent Classification (IPC), which is an internationally recognized hierarchical classification system. We computed this variable using the subclass level of the IPC. Novel technologies were calculated as the number of new technology 'subclasses' that were entered in the previous 3 years and a company was assumed "…to have entered a new subclass when it first applies for a patent in a subclass in which it had not patented in the previous 4 years" (Ahuja and Lampert, 2001, p. 533). This four-year time window results from the fact that technological knowledge depreciates rapidly: not being active in a technology subclass for a considerable period of time will significantly shrink a company's viable knowledge in that technological field. A time window of 4 to 5 years is considered an appropriate time span over which the technology is valuable for a company in high-tech industries (Stuart and Podolny 1996, Ahuja 2000).

Ahuja and Lampert (2001) define pioneering technologies as technologies that do not build on prior technologies. Patent regulations require companies to indicate how much they are indebted to the technological heritage by citing the patents they build on. Companies that apply for a patent that cite no other patents are exploring technological fields that have been left untouched so far. Therefore this variable is computed as the number of a company's patents that cite no other patents.

Control variables

We included four types of dummy variables. A first variable indicates in which economic block the company is headquartered. Following the Triad-concept of the world economy, a company can be headquartered in North America, Asia or Europe - the default is North America. Firms from a different home country may differ in their propensity to patent. Next to that, Asian and European firms may be less inclined to patent in the USA even when the semiconductor industry is widely recognized as a global industry.

Annual dummy variables were included to capture changes over time in the propensity of companies to patent their innovations. The number of ASIC-technology related patents increased from 50 patents in 1988 up to 342 in 1995. In 1996 the number dropped again to 289 patents. Part of this growth is the result of the growing importance of ASIC-products and the accelerating changes in this technological field. Moreover, firms are increasingly aware of the earnings they can reap from by improving intellectual property management (Grindley and Teece, 1997; Teece, 1998; Rivette and Kline, 2000).

Next, dummy variables were used to indicate which type of ASIC-producer a company is. Firms can be involved exclusively in the production of gate arrays, standard cells or PLDs, or they can be involved in more segments at the same time. Segments are important in the sense that firms in each segment face different technologies, different competitors and different competitive or technological dynamics. Therefore, firms can vary in their propensity to patent simply because they are active in other segments.

A last dummy variable is included to control for possible biases due to the fact that some large companies produce ASICs only for their internal needs (captive market), i.e. for internal supply as parts in their electronic systems. These captive producers are a small minority of ASIC-producing companies but are nonetheless important in terms of technological capabilities (e.g. IBM and DEC). They establish technological alliances for the same reasons as ASIC-vendors.

We furthermore included two organizational variables. First, the natural logarithm of 'corporate sales' was included as a control variable. Large companies have the possibility to invest large amounts of money in R&D. Assuming that there exists a positive correlation between technological input and output (Pakes and Griliches, 1984) large firms will have a higher rate of innovation than small firms[11]. The second control variable is the natural logarithm of the ASIC-sales of a company. Firms with a considerable stake in the ASIC-market can defend or improve their market position by

---

[11]   No R&D figures were available for the few privately owned companies in the sample. However, corporate sales are a good proxy for R&D expenditures: for the companies of whom figures where available the correlation between sales en R&D expenditure was 0.91.

rejuvenating or reinforcing their technological capital. This, in turn, requires a high rate of innovation.

Finally, we introduced the annual growth rate of the ASIC market. High growth rates offer companies new economic opportunities stimulating them to invest more in R&D, which in turn should lead to more patents granted to the firm. As a result, we expect a positive coefficient for this variable.

Model specification and econometric issues

The dependent variable is a count variable and takes only nonnegative integer values - i.e. the number of patents a firm filed for in a particular year. A Poisson regression approach provides a natural baseline model for such data (Hausman, Hall and Griliches, 1984; Henderson and Cockburn, 1996). Since we use pooled cross-section data with several observations on the same firms at different points in time, we modeled the data using a random effects Poisson estimator with a robust variance estimator.

The basic Poisson model for event count data can be written as follows:

$$\Pr(Y_{it} = y_{it}) = \frac{\exp(-\lambda_{it})\lambda_{it}^{y_{it}}}{y_{it}!} \tag{1}$$

where the parameter λ_{it} represents the mean and the variance of the event count and y_{it} the observed count variable. It is furthermore assumed that:

$$\lambda_{it} = \beta' x_{it} \tag{2}$$

with x_{it} being a vector of independent variables.

The above specification assumes that the mean and variance of the event count are equal. However, for pooled cross-section count data the variance often exceeds the mean. This overdispersion is particularly relevant in the case of unobserved

heterogeneity[12]. Therefore, a random effects Poisson estimator with robust variance estimator is used: it does not assume within-firm observational independence for the purpose of computing standard errors. For the random effects Poisson estimator equation (2) is changed into:

$$\lambda_{it} = \beta'x_{it} + u_i \qquad\qquad (3)$$

where u_i is a random effect for the ith firm.

Unobserved heterogeneity may be the result of differences between companies in their innovation generating capabilities, and as a consequence, also in their propensity or ability to patent. Such unobserved heterogeneity, if present and not controlled for, can lead to overdispersion in the data or serial correlation. Including the sum of alliances that a firm entered in the last four years (moving window approach) as an additional variable is a common method of controlling for unobserved heterogeneity (Heckman and Borjas, 1980).

Part of the differences between companies or between different years can be captured by including dummy variables in the model. First, the propensity to patent may be partly determined by the nationality of ASIC-producing companies. It is for instance reasonable to assume that Asian or European companies are less inclined to file for patent in the USA. Similarly, we introduced annual dummy variables to account for changes over time: they may capture the ever growing importance of intellectual capital forcing companies to file more patents over the years, or macroeconomic conditions, that may affect the ASIC industry as a whole.

RESULTS

Table 3 presents a correlation matrix and descriptive statistics for the different variables. Table 4 shows the results from the random effects Poisson regressions testing the different hypotheses.

---

[12] The presence of overdispersion does not bias the regression coefficients but the computed standard errors in the Poisson regression are understated, so that the statistical significance is overestimated.

Model 1 in table 4 functions as a baseline model and includes the three types of dummy variables (annual dummy variables are not reported), control variables such as corporate sales, ASIC-sales, annual market growth rate, and the technological capital (cumulative patent count) as an unobserved heterogeneity control variable. In this model, the existing technological capital of a company has a positive and highly significant effect on its innovative performance. This supports the first hypothesis: companies that have an extensive technological capital get relatively more patents than other companies[13].

Firm size (corporate sales) also has a positive and significant impact on the rate of innovation: this suggests that large companies are technologically and financially better equipped to innovate in the ASIC technology field. As ASICs are an intrinsic part of semiconductor technology, this positive coefficient may also point to potential economies of scope in R&D in large, diversified companies. Next, ASIC-sales have a positive and significant effect on the patent rate indicating that companies with a considerable stake in ASIC-market also stronger invest in technology, which, in its turn, invigorates its competitive advantage. Annual dummy variables have no significant impact. The same holds for captive producers and the ASIC market growth. The significant coefficients of some industry segment indicate that the patenting rate is not homogenous for the whole ASIC market: however, the impact is no longer significant when additional independent variables are included in other models. Asian firms have a similar patent rate as their American counterparts, but European firms patent significantly less. Finally, overdispersion is a feature of our data: the dispersion parameter α is significantly different from zero indicating that the assumptions of a simple Poisson model do not hold and that we have to allow for overdispersion. A random effects Poisson estimator is an appropriate way to do so.

Model 2 includes the technology alliances formed by each company during the last five years. We also included the squared term because the 2nd hypothesis suggests an inverted-U shaped relationship between the patent rate and the technological capital of a company. The findings strongly support this hypothesis: firms at intermediate levels

of embeddedness have the highest rate of innovation. Firms with poorly developed alliance networks as well as overembedded firms have lower rates of innovation.

Model 3 adds the interaction term between 'social capital' and 'technological capital' in order to understand how they jointly affect the rate of innovation of companies. The negative and highly significant coefficient corroborates hypothesis 3 and 4. Before we explain their joint effect on the rate of innovation we first have a look at their partial effects.

To demonstrate the impact of both types of capital we first focus on their partial effects on the rate of innovation (i.e. multiplier of the patent rate)[14]. Technological capital moderates the relationship between social capital and the rate of innovation of the firm. This basically has two consequences. First, a larger technological capital decreases the positive impact of social capital on the rate of innovation. In other words, companies with small internal technological capabilities – e.g. start-ups, technological laggards or incumbents that want to get access to a new technology developed by other companies - profit most from their network of technological alliances. Second, higher technological capital requires lower social capital to 'maximize' the rate of innovation.

Similarly, social capital moderates the impact of prior technological capital on the rate of innovation of a company. The relationship is positive for companies that did not establish a network of alliances. It gradually drops the stronger the company is embedded in its alliances network. The relationship becomes negative for companies that are highly embedded – according to model 3 the relationship becomes negative when the company has more than 16 'weighted' technology alliances. Companies that are moderately embedded in an alliance network can tap from the internal technological resources as well as from the knowledge of their partners: their social capital weakens the relation between prior technological capital and the current rate of innovation.

---

[13]   Poisson regressions assume a multiplicative relationship between the dependent variable and the regressors, so that the partial effect of a variable can be understood as a multiplier rate.

[14]   The partial effect of the prior technical capital (TC) in Table 4, Model 3 is $\exp[TC(0.0262-0.0016SC)]$, where SC is the social capital. The partial effect of social capital is $\exp[SC(0.0994-0.0017SC-0.0016TC)]$.

The total impact of both types of capital on the rate of innovation is visualized in figure 6:

Insert here figure 6

The graph compares the patenting rate of companies with no technological and social capital – the benchmark - to patenting rates of companies that have invested previously in one or both types of capital. A positive (negative) patenting rate indicates that the rate of innovation of a company is higher (lower) than that of the benchmark.

The figure shows a number of interesting points. First, there is a 'curve of optimal solutions' maximizing the rate of innovation for each ratio of technological and social capital: left (right) of that curve companies can improve their rate of innovation by increasing (decreasing) their technological or/and social capital. Moreover, the 'optimal' size of the alliance network decreases with an increase of technological capital. If a company has no patents the optimal number of 'weighted' alliances is 29. This number is reduced to 6 alliances when the company has a technological capital of 50 patents. Companies can improve their rate of innovation by investing in social or/and technological capital when the size of their existing internal technological capabilities and social network is small. Hence, technological capital and social capital have mutually reinforcing effects on the rate of innovation. On the contrary, when a company has strong internal technological resources and an extensive alliance portfolio it can only improve its rate of innovation by reducing its alliance network. In that case the two types of capital are substitutes as they overlap in the technology they provide to the focal company. These findings corroborate hypothesis 3.

Second, the plane in figure 6 has a typical saddle shape. The rate of innovation reaches its highest values for two types of strategies: the first strategy is based on relatively high levels of social capital combined with low levels of technological capital. The other strategy in contrast combines strong internal technological capabilities with a minimum of social capital. Hence, these two strategies may successfully coexist in an industry and strategies that are based on equal emphasis of

22

both types of capital are clearly less successful in terms of technological performance. These results provide strong support to hypothesis 4.

Third, firms may overinvest in social capital as has been argued in the literature (Kogut *et al.*, 1992; Harrigan, 1985): there exists an area in figure 6 where the effect of social capital is negative. For companies with no patents this area starts at high levels of embeddedness (59 'weighted' alliances) but this threshold decreases with the increase of technological capital of a company.

Model 4 introduces the innovative performance of the alliance partners. The positive but only weakly significant coefficient indicates that we have some support – although not very convincing – that a company benefits from the technological strengths of its alliance partners. Other variables held constant a one-standard deviation increase in the innovative performance of a firm's alliance partners results in an 8.2 percent increase in the rate of innovation (= $\exp(0.00061*129.48)$ = 1.08219).

As a result we could state that companies connected to technologically advanced partners seem to innovate at a higher rate than those connected to less prominent companies. However, we need to be cautious about these outcomes. There is a high bivariate correlation between the total number of alliances a company established during the previous five years and the accumulated innovative performance scores of its partners over that same period. Therefore we executed the same two additional steps as Stuart (2000) to test whether or not this result is driven by collinearity. First, we omitted the variables based on the cumulative technological alliances (social capital). In that case, the coefficient of the 'innovative performance of the partners'-variable remains positive but is no longer significant (not reported). Second, we replaced the variable 'innovative performance-of-partners' in Model 4 with the 'average innovative performance score computed over the set of partners in each firm's alliance portfolio' (Stuart, 2000: p 803). The advantage of this variable is that even though it is not correlated with the total count of alliances ($r = 0.02$), it still gives a flavor of the innovative performance of the alliance partners. Again, the coefficient is positive but not significant. As a result, it is not safe to claim any support for hypothesis 5.

Model 5 tests the two final hypotheses. We have argued that firms experimenting with novel technologies are more likely to have a higher rate of innovation. These firms are able to value the potential of novel technologies in a more accurate way. They perceive the potential threats of disruptive technologies more easily, and they are more open to new avenues for research. However, too much experimentation with unfamiliar technologies is counterproductive: it should be in balance with the exploitation of familiar technologies. In line with this argument we expect a positive sign for the coefficient of the 'novel technologies'-variable and a negative sign for the squared term. Model 5 indicates strong support for hypothesis 6. Moreover, the magnitude of the effect is substantial: other variables held constant, one-standard deviation increase above the mean in the experimentation with novel technologies results in a 26.5 percent increase in a company's rate of innovation[15].

Finally, hypothesis 7 suggests that experimenting with pioneering technologies increases the rate of innovation of a company. The results in Model 5 support this hypothesis. A one-standard deviation increase in the experimentation of pioneering technologies leads to a 14.4 percent (=exp[1.3429*0.10]) increase in the rate of innovation. Hence, companies that successfully patented a 'pioneering technology'-innovation increase their rate of innovation in the subsequent years.

DISCUSSION AND CONCLUSIONS

The increasing requirements of the organizational environment have forced companies in high tech industries to establish networks of technology alliances. The internal development of technological resources is interwoven with the external acquisition of technologies through alliances. Both technological and social capital determine the rate of innovation of companies. In the literature, both types of capital have been conceived as complements: they are mutually reinforcing each other's

---

[15] The partial effect of the novel technologies (NT) in Table 4, Model 5 is exp[NT(0.2229 - 0.023.NT)]. For an average company this implies a rate of innovation increase of 19.1 percent (exp[0.86(0.2229-0.0230*0.86)]). For a company that is highly involved in experimenting with novel technologies (one-standard deviation above the mean) this increase is 45,6 percent (exp[2.17(0.2229-0.0230*2.17]). The highest possible value for the partial effect (71.6 percent) is reached for companies having experimented with 4.85 novel technologies.

effect on the rate of innovation of a company (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998; Duysters and Hagedoorn, 2000).

In this paper we claim that the effect of an increase in the internal technology capabilities of a company or an extension of the alliance portfolio on its rate of innovation depends on the size of its existing technological and social capital. For low degrees of internal technological capabilities and/or small alliance portfolios increases in either one of both types of capital will increase a company's rate of innovation. Technological and social capital are found to mutually reinforce each other's impact on the technological performance of a company. However, we also found strong empirical support for the change in interaction between both types of capital in the case technological capabilities and the alliance network of a company increase. At high levels, technological and social capital are substitutes: the company with strong technological resources does not need an extensive portfolio of alliances to come up with a strong technological performance. Similarly, companies that learned how to acquire technology from their allies can curtail their internal research and development efforts compared to companies with a small alliance network.

We also found strong support for the possibility of local equilibriums. Two main strategies are found to provide an optimal rate of innovation. The first emphasizes the development of strong internal technological resources in combination with a small alliance portfolio. The other emphasizes the establishment of an extensive alliance network supported by a minimal amount of technological capital.

Stuart (2000) argued that the technological performance of a company is not so much determined by the size of the alliance network but rather by the characteristics of the focal firm's alliance partners. Contrary to his findings we find no credible support for this claim. It is possible that in the specific context of the ASIC industry the technological prominence of the partners are less important because of the continuous stream of 'competence destroying' innovations by new entrants. Another possibility is that slightly different variables will confirm the importance of technological characteristics of the partners. One possible alternative is to calculate differences between the technological capital of the focal firm and that of its partners.

Finally, companies that experiment with novel and pioneering technologies are found to have a higher rate of innovation in subsequent years. This is an interesting finding because it indicates that companies, which almost exclusively focus on the exploitation of their existing technologies, are likely to get trapped in their own technological competences. This supports the idea of Leonard-Barton (1992) that core competencies can turn into core rigidities if companies are not rejuvenating their existing capabilities by exploring new technological fields.

This paper clearly contains a number of limitations. One important limitation is that we did not model the 'interorganizational absorptive capacity' of companies explicitly. We assumed (and found empirical evidence) that the technological capital in a company has a moderating effect on the relationship between its social capital an its rate of innovation. Modeling explicitly the industry and organizational factors that have an impact on the absorptive capacity of a company could improve our understanding of the interaction between technological capital and alliance portfolios.

Future research on the dyadic level (dyad-year as unit of observation) could also complement the firm level analysis about the relationship between technological resources and alliance networks. An analysis on the dyadic level allows us to focus on the question how the probability of the formation of new alliances is affected by (the difference between) the existing technological capital of the allying companies.

REFERENCES

Abernathy, W. and Clark, K. (1985); "Innovation: mapping the winds of creative destruction", *Research Policy*, 14, pp. 3-22.

Ahuja, Gautam (2000); "The duality of collaboration: inducements and opportunities in the formation of interfirm linkages", *Strategic Management Journal*, Vol 21(3), pp. 317-343.

Ahuja, Gautam and Lampert, Curba M. (2001); "Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions", *Strategic Management Journal*, 22 (6-7), pp. 521-543.

Albert M., Avery D., Narin F. and McAllister P. (1991); Direct validation of citation count as indicators of industrially important patents, *Research Policy*, 20 (3), pp. 251-259.

Basberg, B.L. (1987); "Patents and measurement of technological change: A survey of the literature", *Research Policy*, 16 (2-4), pp. 131-141.

Baum, Joel A.C. and Oliver, C (1991); "Institutional linkages and organizational mortality", *Administrative Science Quarterly*, 63, pp. 187-218.

Baum, Joel A.C., Calabrese Tony and Silverman, Brian (2000); "Don't go it alone: Alliance network composition and start ups' performance in Canadian biotechnology", *Strategic Management Journal*, Vol. 20, No. 3, pp. 267-294.

Bower, J.L. and Christensen, C.M. (1995); "Disruptive technologies: Catching the wave", *Harvard Business Review,* January-February, pp. 43-53.

Christensen, Clayton M. and Overdorf, Michael (2000); "Meeting the challenge of disruptive change", *Harvard Business Review*, March-April, pp. 66-76.

Cohen, Wesley M. and Levinthal, Daniel (1990); "Absorptive capacity: A new perspective on learning and innovation", *Administrative Science Quarterly,* 35, pp.128-152.

Conner, K., Prahalad, C.K. (1996). "A resource-based theory of the firm: Knowledge versus opportunism", *Organization Science* **7**(5): 477-501.

Contractor, F. and P. Lorange (eds.) (1988); *Cooperative Strategies in International Business*, Lexington, MA: Lexington Books.

Dierickx, I. and Cool, K. (1989); "Asset stock accumulation and sustainability of competitive advantage", *Management Science*, Vol. 35, pp. 1504-1511.

Dosi, G. (1988); "Sources, procedures, and microeconomic effects of innovation", *Journal of Economic Literature*, 26 (3), pp. 1120-1171.

Duysters, Geert and Hagedoorn, John (1993); *The Cooperative Agreements and Technology Indicators (CATI) Information System*, MERIT: Maastricht, 19 p.

Duysters, Geert and Vanhaverbeke, Wim (1996); "Strategic interactions in DRAM and RISC technology: A network approach*", Scandinavian Journal of Management*, Vol. 12 (4), pp. 437-461.

Duysters, Geert and Hagedoorn, John (1996); *External appropriation of innovative capabilities: The choice between strategic partnering and mergers and acquisitions*, MERIT working paper, 2/96-021, 36 p.

Duysters, Geert and Hagedoorn, John (2000); "Core competencies and company performance in the world-wide computer industry", *Journal of High Technology Management Research*, Vol.11, No.1,

Dyer, J. H. and Signh, H. (1998); "The relational view: Cooperative strategy and sources of interorganizational competitive advantage", *Academy of Management Review*, 23(4), pp. 660-679.

Foster, R (1986); *Innovation: The attackers advantage*, Summit Books: New York.

Galaskiewicz, J. and Zaheer, A (1999); "Networks of competitive advantage", *Research in the Sociology of Organizations*, 16, pp. 237-261.

Garud, R. (1997); "On the distinction between know-how, know-why and know-what", *Advances in Strategic Management*, 14, pp. 81-101.

Gomes-Casseres, Benjamin (1996); *The alliance revolution: The new shape of business rivalry*, Harvard university Press, Cambridge, MA.

Grant, R. A. (1997). 'Toward a knowledge-based theory of the firm', *Strategic Management Journal* 17, Winter Special Issue, pp. 109-122.

Grant, R.M and C. Baden-Fuller (1995); "A knowledge-based theory of inter-firm collaboration", *Academy of management Best Paper Proceedings*, pp. 17-21.

Griliches, Z. (1979); "Issues in assessing the contribution of research and development to productivity growth", *Bell Journal of Economics*, 10, pp. 92-116.

Griliches, Z. (1984); *Patents and productivity*, NBER: Chicago, IL.

Griliches, Z. (1990): "Patent statistics as economic indicators: A survey", *Journal of Economic Literature*, 27, pp. 1661-1707.

Grindley, P. C. and D.J. Teece (1997); "Managing intellectual capital: Lisensing in semiconductors and electronics", *California Management Review*, Vol 39, No.2, pp. 8-41.

Gulati, Ranjay (1995); "Social structure and alliance formation patterns: A longitudinal analysis", *Administrative Science Quarterly*, 40(4), pp. 619-652.

Gulati, Ranjay (1999); "Network location and learning: The influence of network resources and firm capabilities on alliance formation", *Strategic Management Journal*, 20(5), pp. 397-420.

Hagedoorn, John and Schakenraad, Jos (1994); "The effect of strategic technology alliances on company performance", *Strategic Management Journal*, 15 (4), pp. 291-309.

Hamel, G. P. (1991); "Competition for competence and interpartner learning within international strategic alliances", *Strategic Management Journal*, Summer Special Issue, 12, pp. 83-103.

Hamel, G.P., Doz, Y., and C.K. Prahalad (1989); "Collaborate with your competitors and win", *Harvard Business Review*, 67 (1), pp. 133-139.

Harrigan, K.R. (1985); *Strategies for joint ventures*, Lexington Books, Lexington, MA.

Hausman J., Hall B. and Griliches, Z. (1984); "Econometric models for count data with an application to the patents-R&D relationship", *Econometrica*, 52, pp. 909-938.

Heckman, J.J. and Borjas, G.J. (1980); "Does unemployment cause future unemployment: definitions, questions, and answers from a continuous time model of heterogeneity and state dependence", *Econometrica*, 48, pp. 247-283.

Henderson, R. and Cockburn, I. (1996); "Scale, scope and spillovers: the determinants of research productivity in drug discovery", *Rand Journal of Eco*nomics, 27 (1), pp. 32-59.

Hoskisson, R, Hitt, M. and Hill C.L.W. (1993); Managerial incentives and investment in R&D in large multiproduct firms", Organization Science, 4 (2), pp. 325-341.

Hoskisson, R, Hitt, M. and Ireland, D. (1994); The effects of acquisitions and restructuring (strategic refocusing) strategies on innovation. In: *The management of corporate acquisitions: International perspectives*, Von Krogh, G. Sinatra, A. and Singh, H. (eds.), MacMillan: Houndsmills, pp. 144-169.

Jaffe, Adam B. (1986); "Technological opportunity and spillovers of R&D: Evidence from firms' patents", *American Economic Review*, 76(5), pp. 984-1001.

Kale, P., Singh, H. and Perlmutter, H. (2000); "Learning and protection of proprietary assets in strategic alliances: Building relational capital", Strategic Management Journal, *Special Issue*, 21, pp. 217-237.

Khanna, T., Gulati, R. and Nohria, N. (1998); "The dynamics of learning alliances: Competition, cooperation and relative scope", *Strategic Management Journal*, 19 (3), pp. 193-210.

Kogut, Bruce (1988); "A study of the life cycle of joint ventures", in F. Contractor and P. Lorange (eds.), *Cooperative Strategies in International Business*, Lexington, MA: Lexington Books, 169-186.

Kogut, Bruce (1989); "The stability of joint ventures: reciprocity and competitive rivalry", *Journal of industrial economics*, 38, pp. 183-198.

Kogut, Bruce and Zander, Udo (1992); "Knowledge of the firm, combinative capabilities, and the replication of technology", Organization Science, Vol 3, No 3, pp. 383-397.

Kogut, Bruce, Weijan Shan and Gordon Walker (1992*); The make-or-cooperate decision in the context of an industry network*, In: Nitin Nohria and Robert Eccles (eds.), Networks and organizations: Structure, form and actions, HBSPress: Bosteon MA, pp. 348-365.

Kogut, Bruce and Zander, Udo (1996); "What firms do? Coordination, identity and learning", *Organization Science,*, 7, pp. 502-518.

Lane, Peter J. and Michael Lubatkin (1998); "Relative absorptive capacity and interorganizational learning", *Strategic Management Journal*, Vol. 19, pp. 461-477.

Lei, D., Hitt, M.A. and Bettis, R. (1996); "Dynamic core competencies through meta-learning and strategic context", Journal of Management, 22 (4), pp. 549-569.

Leonard-Barton, Dorothy (1992); "Core capabilities and core rigidities: A paradox in managing new product development", *Strategic Management Journal*, Summer Special Issue, Vol 13, pp. 111-125.

Levin, Richard C., Cohen W.M. and Mowery, D.C. (1985); "R&D appropriability, opportunity and market structure", *American Economic Review*, 75 (2), pp. 20-24.

Levinthal, Daniel A. and March, J.G. (1981); "A model of adaptive organizational search", *Journal of Economic Behavior and Organization*, Vol. 2, pp. 207-233.

Levinthal, Daniel A. and March, J.G. (1993); "The myopia of learning", *Strategic Management Journal*, Winter Special Issue, 14, pp. 95-112.

Lunn, John and Martin, Stephen (1986); "Market structure, firmstructure, and research and development", *Quarterly Review of Economics and Business*, Vol. 26, No. 1, pp. 31-44.

March, J.G. (1991); "Exploration and exploitation in organizational learning", *Organization Science*, Vol. 2 (1), pp. 71-87.

McClean, William J., (ed.) (1985-1998); *Status 19xx: A report on the integrated Circuit Industry*. Scottsdale, Arizona: Integrated Circuit Engineering Corporation.

Mitchell, W. and Singh, K. (1992); "Incumbents' use of pre-entry alliances befor expansion into new technological subfields of an industry", *Journal of Economic Behavior and Organization*, 18 (3), pp. 347-372.

Mitchell, W. and Singh, K. (1996); "Survival of businesses using collaborative relationships to commercialize complex goods", *Strategic Management Journal*, 17 (3), pp. 169-196.

Mowery, D.C. (ed.) (1988); *International collaborative ventures in the U.S. manufacturing*. Cambridge: Ballinger.

Mowery, D.C, Oxley, J.E. and Silverman, B.S. (1995); *Firm capabilities, technological complementarity, and interfirm cooperation,* Paper prepared for the conference on technology and the theory of the firm, University of Reading, May 14-16.

Nahapiet, J. and Ghoshal, S. (1998); "Social capital, intellectual capital and organizational advantage", *Academy of Management Review*, 23 (2), pp. 242-266.

Narin, F., Noma, E. and Perry, R. (1987); "Patents as indicators of corporate technological strength", *Research Policy*, 16 (2-4), pp. 26-48.

Nohria, Nitin and Carlos Garcia-Pont (1991); "Global strategic linkages and industry structure", *Strategic Management Journal*, 12, 105-124.

Osborn, R.N. and Baughn, C.C. (1990); "Forms of interorganizational governance for multinational alliances", *Academy of Management Journal*, 33, pp. 503-519.

Pakes, Ariel and Griliches, Zvi (1984); Patents and R&D ath the Firm Level: A first look, In: Zvi Griliches (ed.); *R&D, patents and Productivity*, University of Chicago: Chicago, pp. 55-70.

Podolny, J.M. (1994); "Market uncertainty and the character of of economic exchange", *Administrative Science Quarterly*, 39, pp. 458-483.

Podolny, J.M. and Stuart, T.A. (1995); "A role-based ecology of technological change", *American Journal of Sociology*, 100 (5), pp. 1224-1260.

Powell, Walter W., Koput, K.W. and Smith-Doerr L. (1996); "Interorganizational collaboration and the locus of control of innovation: Networks of learning in biotechnology", *Administrative Science Quarterly*, 41(1), pp. 116-145.

Rivette, K. and D. Kline (2000); "Discovering new value in intellectual property", *Harvard Business Review*, January-February, 2000, pp. 54-66.

Rowley, Tim, Dean Behrens and David Krackhardt (2000); "Redundant governance structures: An analysis of structural and relational embeddedness in the steel and semiconductor industries", *Strategic Management Journal*, Special Issue, 21 (3), pp. 369-386.

Sahal, D. (1985); "Technological guideposts and innovation avenues", *Research Policy*, 14 (2), pp. 61-82.

Shan, Weijan (1990); "An empirical analysis of organizational strategies by entrepreneurial high-technology firms", *Strategic Management Journal*, 11 (2), pp. 129-139.

Shan, Weijan, Walker, Gordon and Kogut, Bruce (1994); "Interfirm cooperation and startup innovation in the biotechnology industry", *Strategic Management Journal*, Vol 15, pp. 387-394.

Spender, J-C (1996); "Making knowledge the basis of a dynamic theory of the firm", *Strategic Management Journal*, Winter Special Issue, 17, pp. 45-62.

Stuart, Toby E. (2000); "Interorganizational alliances and the performance of firms: A study of growth rates in a high-technology industry", *Strategic Management Journal*, 21 (8), pp. 791-811.

Stuart, Toby E and Podolny, J.M. (1996); "Local search and the evolution of technological capabilities", *Strategic Management Journal*, Summer Special Issue, 17, pp. 21-38.

Stuart, Toby E., Hoang H. and Hybels, R. (1999); "Interorganizational endorsements and the performance of entrepreneurial ventures", *Administrative Science Quarterly*, 44, pp. 315-349.

Teece, David J. (1998): "Capturing value from knowledge assets: The new economy, markets for know-how and Intangible assets", *California Management Review*, Vol. 40 No. 3, pp. 55-79.

Teece, David J., Gary Pisano, and Shuen, Amy (1997): "Dynamic capabilities and strategic management", *Strategic Management Journal*, 18 (7), pp. 509-533.

Tushman, M.L. and Anderson, P. (1986); "Technological discontinuities and organizational environments", *Administrative Science Quarterly*, 31, pp. 439-465.

Utterback, J.M. (1994); *Mastering the dynamics of innovation*, Harvard Business School Press: Boston, MA.

Uzzi, B. (1996); "The sources and consequences of embeddedness for economic performance of organizations: the network effect", *American Sociological Review*, 61, pp. 674-698.

Uzzi, B. (1997); "Social structure and competition in interfirm networks: The paradox of embeddedness", *Administrative Science Quarterly*, Vol 42, pp. 35-67.

Table 1: ASIC definitions

I.   *Semicustom IC:* A monolithic circuit that has one or more customized mask layers, but does not have all mask layers customized, and is sold to only one customer.
> **Gate arrays:** A monolithic IC usually composed of columns and rows of transistors. One or more layers of metal interconnect and are used to customize the chip.
> **Linear array:** An array of transistors and resistors that performs the functions of several linear ICs and discrete devices.

II.   *Custom IC:* A monolithic circuit that is customized on all mask layers and is sold to only one customer.
> **Standard cell IC:** A monolithic circuit that is customized on all mask layers using a cell library that embodies pre-characterized circuit structures.
> **Full custom IC:** A monolithic circuit that is at least partially "handcrafted". Handcrafting refers to custom layout and connection work that is accomplished without the aid of standard cells.

III.   *Programmable Logic Device (PLD):* A monolithic circuit with fuse, antifuse, or memory cell-based logic that may be programmed (customized), and in some cases, reprogrammed by the user.
> **Field Programmable Gate Array (FPGA):** A PLD that offers fully flexible interconnects, fully flexible logic arrays, and requires functional placement and routing.

Electrically Programmable Analog Circuit (EPAC): A PLD that allows the user to program and reprogram basic analog devices.

Tabel 2: Definitions of dependent and independent variables

Variable name	Variable description	Expected effect
Number of patents	Count of the number of patents a firm filed for in the current year (t). Only patents that were granted to the company are taken into consideration	--------
Cumulative patents$_{t-1}$	Count of the number of ASIC-related patents that a firm filed for during the previous four years (t-4 to t-1)	Positive
Cumulative technology alliances$_{t-1}$	Count of the number of technology alliances a firm established in the five previous years (t-5 to t-1)	Positive
(Cumulative technology alliances$_{t-1}$)^2	Squared term of the previous variable	Negative
(Cum. technology alliances $_{t-1}$) * (cum. patents $_{t-1}$)	Interaction between the number of ASIC-related patents a firm file for during the last 4 years and the number of alliances it formed in the previous 5 years	Negative
Innovative performance of alliance partners	Sum of the patent citations received by the firm's alliance partners	Positive
Novel technologies$_{t-1}$	Number of patents filed during the last 3 years in patent classes in which the company had not patented in the previous 4 years	Positive
(Novel technologies$_{t-1}$)^2	Squared term of the previous variable	Negative
Pioneering technologies$_{t-1}$	Number of a firm's patents that cite no other patents	Positive
Log ASIC sales$_{t-1}$	Natural logarithm of the ASIC sales of the firm	Positive
Firm size (log sales)$_{t-1}$	Natural logarithm of the total sales of the firm	Positive
ASIC market growth$_{t-1}$	Annual growth rate of the ASIC market	Positive
Firm is a captive producer	Dummy variable denoting that the firm is not selling ASICs on the market	Negative
Firm is Asian	Dummy variable denoting that the firm is headquartered in Asia	
Firm is European	Dummy variable denoting that the firm is headquartered in Europe	
Firm is GA-producer	Dummy variable denoting that the firm is producing only gate arrays	
Firm is SC-producer	Dummy variable denoting that the firm is producing only standard cells	
Firm is PLD-producer	Dummy variable denoting that the firm is producing only PLDs	
Firm is GA and SC producer	Dummy variable denoting that the firm is producing gate arrays and standard cells	
Firm is GA and PLD producer	Dummy variable denoting that the firm is producing gate arrays and PLDs	

Tabel 3: Descriptive statistics and correlation matrix

	Variable	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Number of patents	1.22	3.40	0	42																
2	Cumulative technology alliances$_{t-1}$	4.05	6.90	0	38	0.25															
3	Cumulative patents$_{t-1}$	3.93	8.15	0	72	0.67	0.33														
4	Log ASIC sales$_{t-1}$	2.95	2.03	-0.65	7.43	0.38	0.43	0.49													
5	ASIC market growth$_{t-1}$	0.14	0.03	0.10	0.21	-0.16	0.09	-0.02	-0.06												
6	Firm size (log sales)$_{t-1}$	6.20	3.30	-0.65	12.60	0.19	0.40	0.37	0.52	-0.02											
7	Novel technologies$_{t-1}$	0.86	1.31	0	11	0.48	0.39	0.61	0.41	-0.05	0.36										
8	Pioneering technologies$_{t-1}$	0.08	0.10	0	2	0.12	0.01	0.11	0.11	0.12	0.12	0.12									
9	Firm is a captive producer	0.12	0.32	0	1	-0.01	-0.01	0.01	-0.31	-0.01	0.21	-0.00	0.01								
10	Innovative performance of alliance partners	46.91	129.48	0	1251	0.26	0.48	0.36	0.28	0.01	0.26	0.37	0.01	-0.01							
11	Firm is Asian	0.22	0.42	0	1	0.02	0.00	0.17	0.14	0.00	0.40	0.10	0.12	-0.04	-0.01						
12	Firm is European	0.17	0.38	0	1	-0.11	0.15	-0.12	-0.01	0.01	0.10	-0.12	-0.04	0.10	0.04	-0.25					
13	Firm is GA-producer	0.12	0.32	0	1	-0.10	-0.16	-0.14	-0.07	0.00	-0.13	-0.13	0.01	-0.03	-0.12	-0.12	-0.14				
14	Firm is SC-producer	0.18	0.39	0	1	-0.13	-0.15	-0.16	-0.12	-0.03	-0.20	-0.19	-0.04	-0.01	-0.12	-0.21	0.14	-0.17			
15	Firm is PLD-producer	0.07	0.25	0	1	0.31	-0.01	0.17	0.16	-0.02	-0.13	0.13	-0.02	-0.10	0.09	-0.14	-0.12	-0.10	-0.13		
16	Firm is GA and SC producer	0.30	0.46	0	1	0.06	0.07	0.17	0.44	-0.00	0.38	0.24	0.10	-0.13	0.09	0.35	-0.04	-0.23	-0.31	-0.17	
17	Firm is GA and PLD producer	0.08	0.09	0	1	0.04	0.09	0.00	0.07	0.04	0.00	0.03	-0.01	-0.03	0.02	-0.05	-0.04	-0.03	-0.04	-0.02	-0.06

N = 830 observations
All correlations with magnitude $> |0.077|$ are significant at the 0.05 level

Tabel 4: Determinants of the patent rate of ASIC producers, 1988-1996

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Cumulative patents$_{t-1}$	0.0162***	0.0153***	0.0262***	0.0292***	0.0309***
	(0.0048)	(0.0052)	(0.0053)	(0.0054)	(0.0073)
Cumulative technology alliances$_{t-1}$		0.0786***	0.0994***	0.0965***	0.0872***
		(0.0172)	(0.0201)	(0.0246)	(0.0302)
(Cumulative technology alliances$_{t-1}$)^2		-0.0018***	-0.0017**	-0.0017**	-0.0012*
		(0.0006)	(0.0007)	(0.0008)	(0.0007)
(Cum. technology alliances$_{t-1}$) * (cum. patents$_{t-1}$)		-0.0016***	-0.0019***	-0.0020***	
			(0.0003)	(0.0003)	(0.0003)
Innovative performance of alliance partners				0.00061*	
				(0.00033)	
Novel technologies$_{t-1}$					0.2229**
					(0.0888)
(Novel technologies$_{t-1}$)^2					-0.0230*
					(0.0135)
Pioneering technologies$_{t-1}$					1.3429**
					(0.5546)
Log ASIC sales$_{t-1}$	0.1269**	0.1087***	0.1212**	0.1319**	0.1281*
	(0.0541)	(0.0575)	(0.5874)	(0.0584)	(0.0658)
Firm size (log sales)$_{t-1}$	0.2936***	0.2381***	0.1935***	0.1841***	0.1554***
	(0.0569)	(0.0535)	(0.0553)	(0.0552)	(0.0568)
ASIC market growth$_{t-1}$	8.3684	6.9522	5.294	7.3250	3.6514
	(60.7947)	(66.9714)	(76.8344)	(63.1954)	(93.0791)
Firm is a captive producer	-0.5178	-0.3482	-0.1770	-0.1305	-0.0460
	(1.0519)	(0.9906)	(0.3082)	(0.9108)	(0.8288)
Firm is Asian	0.9609	-0.6905	-0.4957	-0.4454	-0.3269
	(0.8214)	(0.7896)	(0.8021)	(0.7879)	(0.6925)
Firm is European	-1.7333***	-1.6781***	-1.6275**	-1.6088**	-1.4219**
	(0.6326)	(0.6643)	(0.7011)	(0.6874)	(0.6314)
Firm is GA-producer	0.5137*	0.5375*	0.4132	0.3429	0.0813
	(0.2772)	(0.2990)	(0.3447)	(0.3438)	(0.3250)
Firm is SC-producer	-0.5131**	-0.4198*	-0.4573*	-0.4677**	-0.3706
	(0.2343)	(0.2248)	(0.2425)	(0.2341)	(0.2976)
Firm is PLD-producer	0.8335	0.8496*	0.7167	0.6707	0.6608
	(0.5972)	(0.4697)	(0.4776)	(0.4778)	(0.4762)
Firm is GA and SC producer	-0.1456	-0.0250	-0.1116	-0.1777	-0.2186
	(0.1541)	(0.1544)	(0.1608)	(0.1697)	(0.1915)
Firm is GA and PLD producer	0.8286	0.3909	0.3623	0.3272	0.4156
	(1.4550)	(2.4542)	(2.7874)	(2.7063)	(2.8703)
Constant	-4.3035	-4.1684	-3.8625	-4.1907	-3.5583
	(11.5597)	(12.7302)	(14.6083)	(12.0047)	(17.6953)
α	1.7460***	1.4786***	1.3206***	1.2837***	0.9574***
	(0.3759)	(0.3376)	(0.3082)	(0.3025)	(0.2508)
Number of firms	99	99	99	99	99
Number of firms-years	830	830	830	830	830
Log-likelihood	370.87	382.50	392.20	394.51	410.38
Chi-squared	741.74	765.00	784.40	789.02	820.75

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

'Year dummy variable'-coefficients are not statistically significant. They are not reported in the table.

The models use a random effects Poisson estimator. The sample is an unbalanced panel with 99 ASIC producers and 830 firm-years (units of observation).

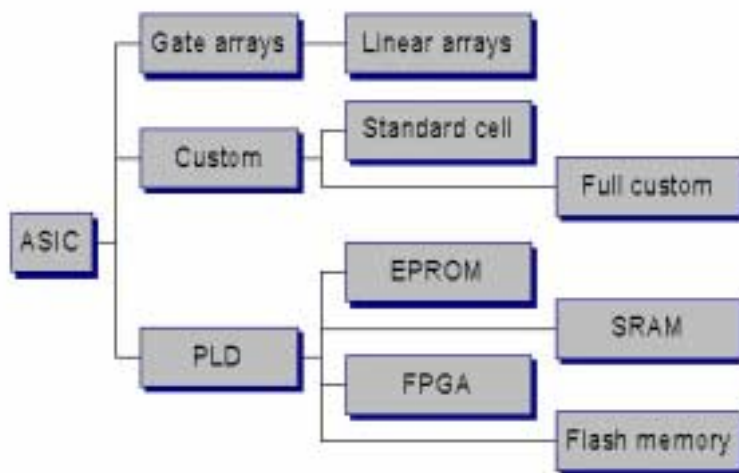# Figure 1: The ASIC technology field
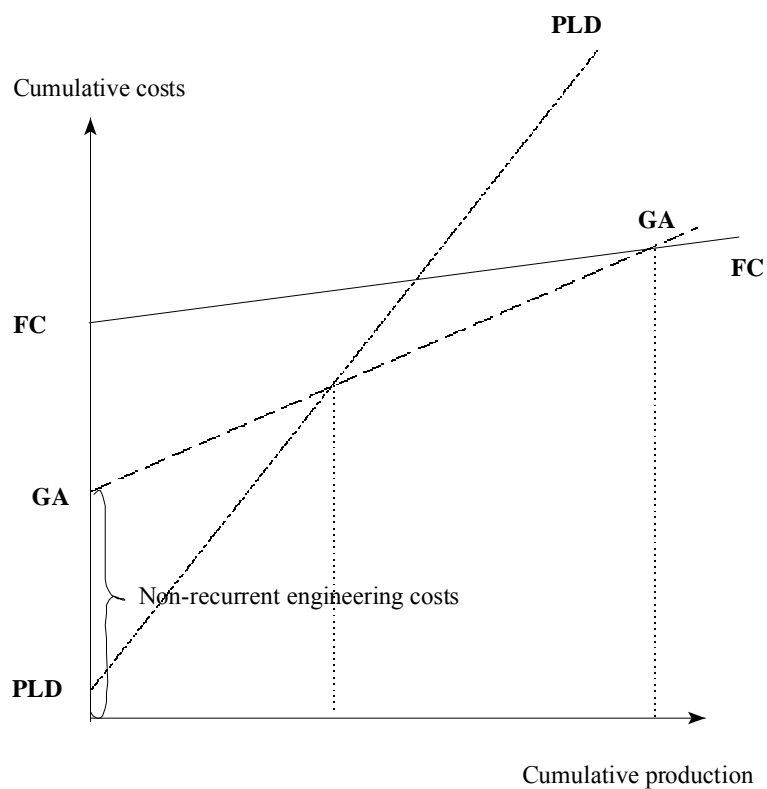

Figure 2: The segments in the ASIC technology field
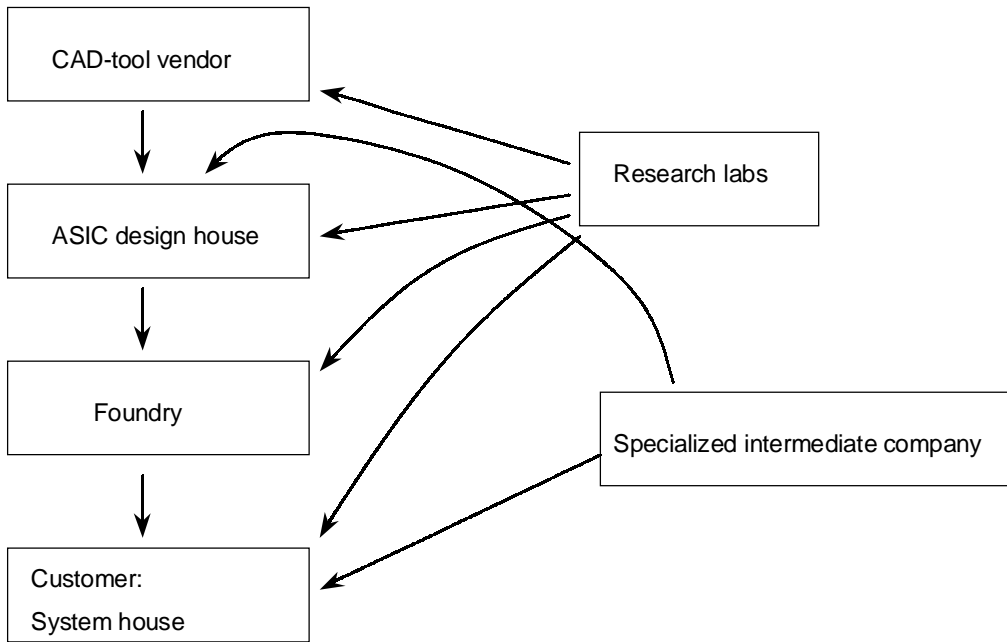
Figure 3: The ASIC technology field

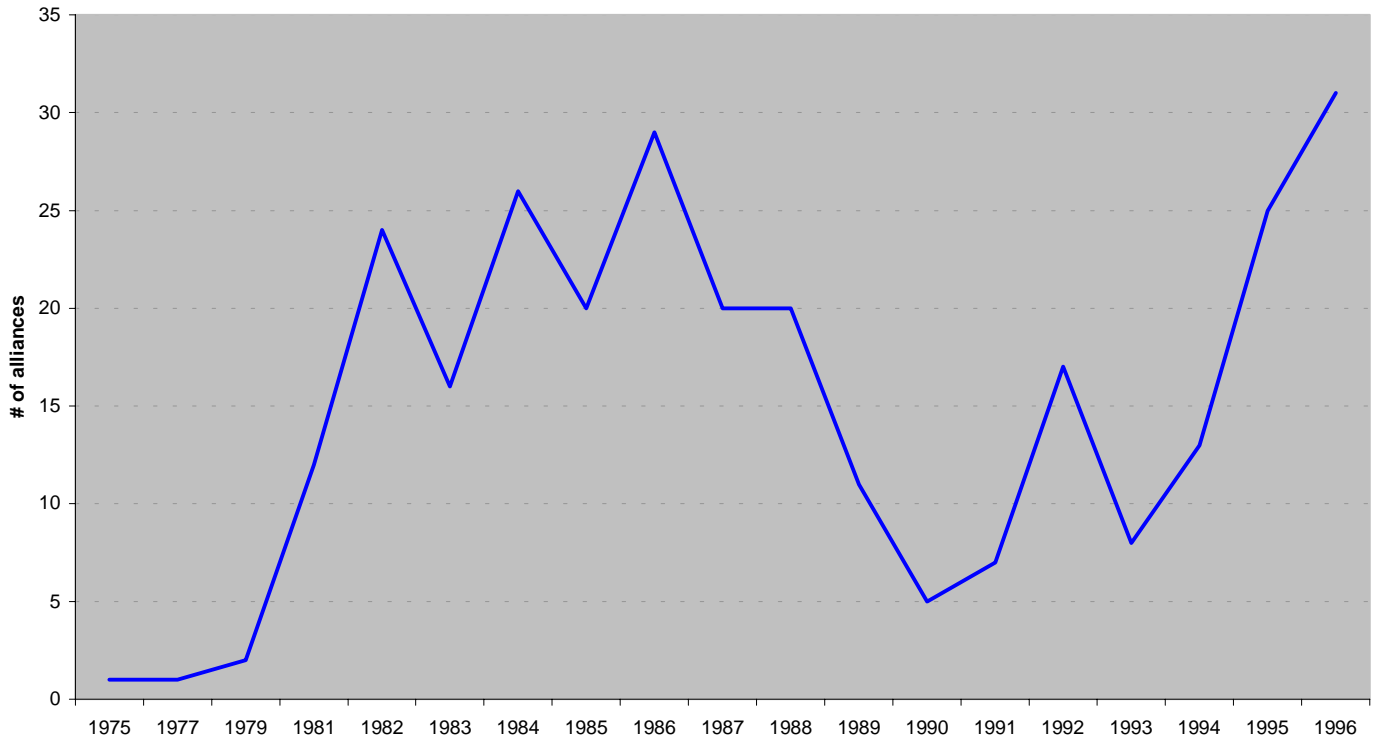# Figure 4: Number of technology based SAs in the ASIC industry

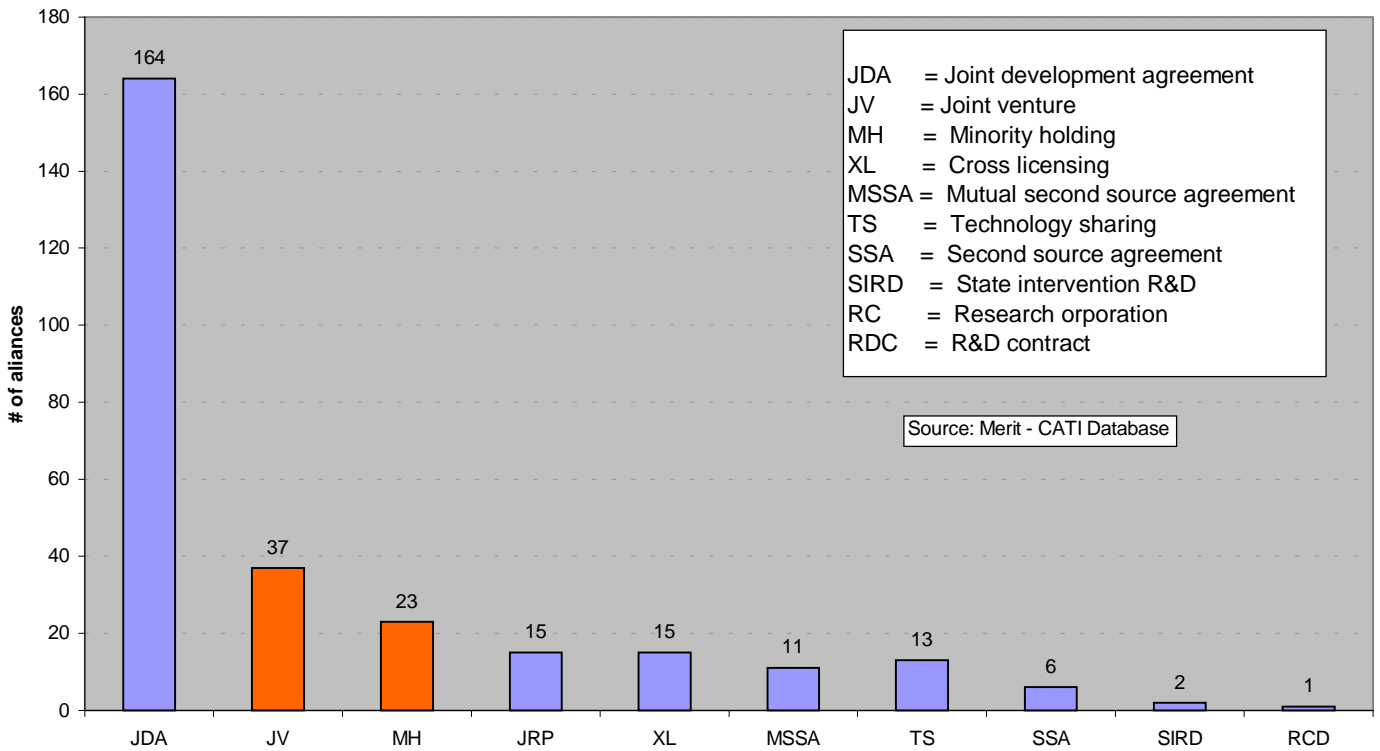## Figure 5: Different types of SAs in the ASIC industry

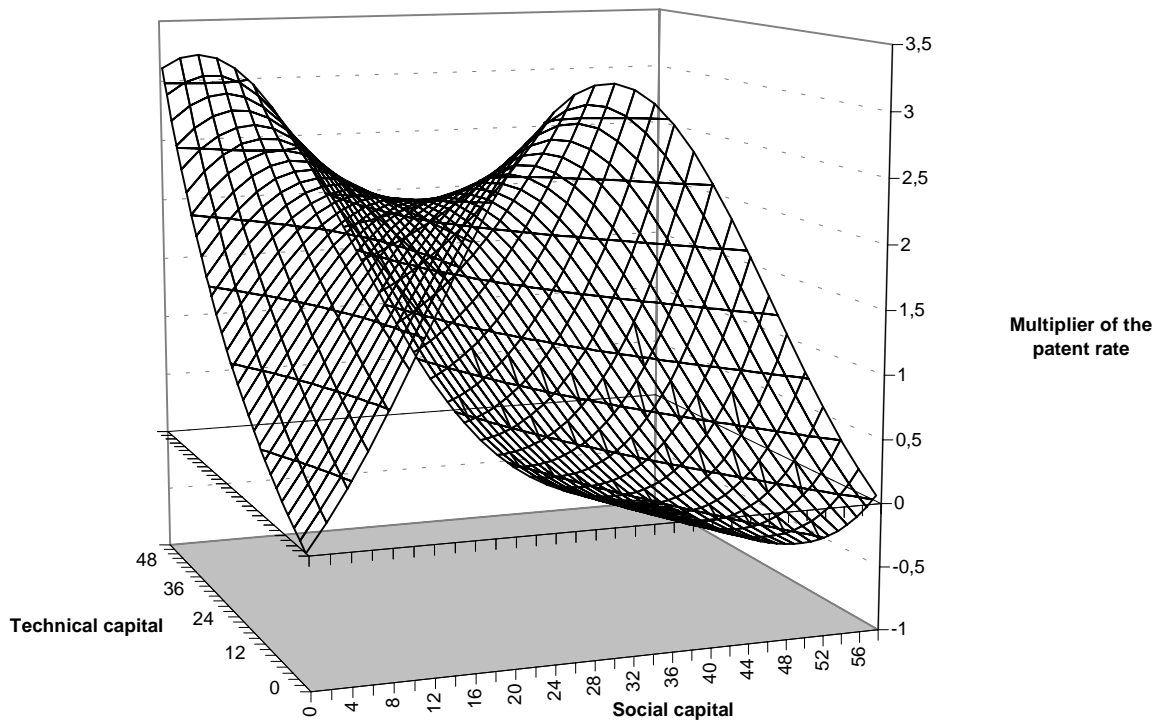|	
JDA	= Joint development agreement
JV	= Joint venture
MH	= Minority holding
XL	= Cross licensing
MSSA	= Mutual second source agreement
TS	= Technology sharing
SSA	= Second source agreement
SIRD	= State intervention R&D
RC	= Research orporation
RDC	= R&D contract

Source: Merit - CATI Database

Figure 6: Impact of social and technical capital on the patent rate

Eindhoven Centre for Innovation Studies

WORKING PAPERS

Ecis working papers (December 2001):

98.1:   Per Botolf Maurseth & Bart Verspagen:
         Knowledge spillovers in Europe and its consequences for systems of innovation

98.2:   Jan Fagerberg & Bart Verspagen:
         Productivity, R&D spillovers and trade

98.3:   Leon A.G. Oerlemans, Marius T.H. Meeus & Frans W.M. Boekema:
         Learning, innovation and proximity

99.1:   Marius T.H. Meeus, Leon A.G. Oerlemans & Jules J.J. van Dijck:
         Regional systems of innovation from within

99.2:   Marcel P. Timmer: Climbing the technology ladder too fast?:
         An international comparison of productivity in South and East- Asian manufacturing, 1963-1993

99.3:   Leon A.G. Oerlemans, Marius T.H. Meeus, Frans W.M. Boekema:
         Innovation and space: theoretical perspectives

99.4:   A. Mukherjee & N. Balasubramanian:
         Technology transfer in a horizontally differentiated product-market

99.5:   Marius T.H. Meeus, Leon A.G. Oerlemans & J. Hage:
         Sectoral patterns of interactive learning

99.6:   Bart Verspagen:
         The role of large multinationals in the dutch technology infrastructure

99.7:   Leon A.G. Oerlemans & Marius T.H. Meeus:
         R&D cooperation in a transaction cost perspective

99.8:   Gerald Silverberg & Bart Verspagen:
         Long memory in time series of economic growth and convergence

99.9:   B. Bongenaar & A. Szirmai:
         The role of a research and development institute in the development and diffusion of technology

99.10:   M.C.J. Caniëls & B. Verspagen:
         Spatial distance in a technology gap model

99.11:   J.I.M. Halman, J.A. Keizer & X.M. Song:
Perceived risks in product innovation projects: development of a risk skeleton

99.12:   A. Mukherjee:
Subsidy and entry: role of licensing

99.13:   M.C.J. Caniëls & B. Verspagen:
The effects of economic integration on regional growth, an evolutionary model

00.01:   O. Lint:
The primary assessment tool at Philips Electronics:
Capturing real options and organizational risk in technology portfolio management

00.02:   O. Lint & E. Pennings:
The recently chosen digital video standard: playing the game within the game

00.03: A. Mukherjee & E. Pennings:
Imitation, patent protection and welfare

00.04:   J. Hagedoorn & G. Duysters
The effect of mergers and acquisitions on the technological performance of companies in a high-tech environment

00.05:   O. Lint & E. Pennings:
The V-shaped value evolution of R&D projects

00.06:   H. Romijn:
Technology support for small industries in developing countries:
A review of concepts and project practices

00.07:   B.Verspagen & W. Schoenmakers:
The spatial dimension of knowledge spillovers in
Europe: evidence from firm patenting data

00.08:   B. Verspagen:
Growth and structural change: trends, patterns and policy options

00.09:   O. Lint:
Retrospective insights from real options in R&D

00.10:   O. Marsili:
Technological regimes and sources of entrepreneurship

00.11:   A. Nuvolari:
The 'machine breakers' and the industrial revolution

00.12   B. Verspagen:
Economic growth and technological change: an evolutionary interpretation

00.13   M. Albaladejo & H. Romijn:
Determinants of innovation capability in small UK firms: an empirical analysis

00.14   O. Marsili:
Sources of Concentration and Turbulence in Evolutionary Environments:
Simulations of Learning and Selection

00.15   R. Bekkers, G. Duysters, B. Verspagen:
Intellectual property rights, strategic technology agreements and market structure. The case of the GSM