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Technological capability building through networking strategies within high-tech industries

Wim Vanhaverbeke[1], Bonnie Beerkens[2] and Geert Duysters[3]

Abstract

Learning through networks has been considered as an important 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 empirical evidence for decreasing marginal returns on social capital. 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 the patent portfolio and network of alliances are extensive, companies risk to over-invest since optimal levels of social capital become smaller at higher levels of technological capital and the marginal benefits of investing in technological capital decreases the higher the levels of social capital. Finally, we find empirical evidence that companies that explore novel and pioneering technologies have higher levels of innovation performance in subsequent years than companies that solely invest in incremental innovations.

Keywords: Strategic Alliances, Networks, Innovation

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INTRODUCTION

This study investigates the relationship between the technological performance of companies in high-tech industries and their technological and social capital. More specifically, we focus on three main research topics. First, we consider whether a firm's technological and social capital - i.e. its patent stock and portfolio of technology alliances - are mutually enforcing factors that together determine the rate of innovation, or, alternatively, whether they can be considered as substitutes. We also address the question of whether an optimal mix of resources exists, which results into above average technological performance. 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, gave 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 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 *et al.*, 1994; Powell *et al.*, 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 increasingly 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 tap into other companies' technological assets. Market transactions are generally considered to be 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 increasingly based on a combination of internal and external learning: internal learning comes about by the internal development of new products and through internal R&D processes, external learning thrives on 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[4].

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

[4] 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 *et al.*, 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 means of 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 larger the technological capabilities a firm has accumulated in the past the higher its current rate of innovation.*

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 rapidly 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 technological resources across industries or technological fields. Alliances are often

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1986). In what follows we focus on the relationship between technical and social capital and 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 suggests the following hypothesis:

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

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

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ignore the linkages with commercial capital.

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 benefit 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 by 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 *et al.*, 1989; Kale *et al.*, 1999; Khanna *et al.*, 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. One can imagine that 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.*

The combination of hypotheses 2 and 3 entails the possibility 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[5]. 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 technological assets offers a company the best opportunities to learn and thus to invigorate its competitive position.

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5 Similarly, Baum *et al.* (2000) argue that the performance of biotechnology start-ups is positively influenced by the technological capabilities of the partnering companies.

Hypothesis 5: *The stronger the technological capabilities of a company's alliance partners, the higher its innovation rate.*

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)[6]. 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

6 Learning traps (Levinthal and March, 1993) are closely related to the concept of competency traps (Levitt and March, 1988). "Competency traps are defined to occur 'when favorable performance with an inferior procedure leads an organization to accumulate more experience with it, thus keeping experience with a superior procedure inadequate to make it rewarding to use' (Levitt and March, 1988: 322). Learning traps, on the other hand, embody the conflict between routines that enable the organization to perform well in the short run but may position the organization unfavorably for the future. Thus, while competency traps entail choices between two procedures or routines targeted towards the same outcome, the learning traps we discuss here are about the implications of the same routines for two different outcomes such as reliable and predictable outputs that are necessary for immediate or short-run performance, and breakthrough inventions that may form the basis of superior performance in the future." (Ahuja and Lampert, 2001: 523)

(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 Raynor, 2003) 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 is related in a curvilinear way (inverted-U shaped) to its exploration of novel technologies in the past.*

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. 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 *et al.*, 1993; Hoskisson *et al.*, 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 - 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 is positively related to its success in pioneering technologies in the past.*

EMPIRICAL SETTING

Definition and characteristics

The hypotheses are 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. In contrast with the general purpose ICs such as DRAMs and microprocessors, ASICs are build to perform only one particular function – e.g. converting digital signals of a CD into music[7].

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

[7] 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. A device which is made for one particular type of system function (e.g. disk-drives, CD-players, video compressing, etc...) 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.

ASIC market is divided into three submarkets. According to the "Integrated Circuit Engineering Corporation" (ICE) the ASIC market includes the following categories of ICs: gate arrays (GA), full custom ICs (FC), 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

A wide range of specific system functions can be fabricated *alternatively* by gate arrays, full custom devices or PLDs. These three ASIC-categories are different devices realising the same system functionalities. As a result, there is almost no affinity between the targeted system function and the type of ASIC to use[8]. ASIC vendors typically have to make a choice between the three ASIC types minimizing the volume-dependent total cost per chip. PLDs are the cheapest solution for low volume ASICs. Once the production volume exceeds the level of a few thousands units, gate arrays become the most interesting ASIC solution. Custom ICs are the most efficient solution for production volumes that exceed several hundred-thousands of ASICs.

Insert Figure 2 here

Different players and motives for technology alliances

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. The structure of the interplay between the different economic actors has not changed in a structural way during the period of observation.

Insert Figure3 here

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8 The only exception is linear arrays, which are used to design analog or mixed (analog/digital) system functions. Linear arrays are applied mainly in the telecommunication and consumer electronics markets, where most signals are analog in nature.

Electronic system manufacturers usually build a foothold in the ASIC market by vertical integration: they want to achieve or sustain a competitive advantage for their electronic systems through proprietary ASIC designs. Electronic system manufacturers also make corporate-wide deals and second-source agreements with foundries. Large system manufacturers have their own ASIC design house and foundry or they acquire one. Vertically integrated system manufacturers still cooperate with specialised design houses because of recurrent peaks in design work. Large, integrated electronic system manufacturers have their own fab-lines. Their ASICs are processed together with standard ICs.[9] Smaller companies set up agreements with different foundries to process their ASICs. Second-source agreements are frequently used in order to ensure availability of ASICs on time and to avoid lock-in situations. Captive producers - e.g., IBM and DEC - also establish second-source agreements because of peaks in demand. As ASIC-designs become increasingly complex, companies establish numerous joint development and cross-licensing agreements. Some ASIC vendors are also active in the CAD-tool market - e.g., VLSI Technology. The CAD-tool market is small, and tool development is very expensive. Installing the same CAD-infrastructure among interacting firms greatly enhances technology transfer. Therefore, numerous strategic alliances are established between ASIC producers and CAD-tool vendors. The CAD-tool market is furthermore characterised by an ongoing process of acquisitions by the largest CAD-tool vendors and entries by *de novo* firms and spin-offs.

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 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. Stand-alone strategies might no longer be viable, even for the largest companies (Duysters and Hagedoorn, 1996).

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[9] Processing ASICs together with standard ICs creates a considerable cost advantage, but is also characterised by disadvantages *vis-à-vis* specialized ASIC-foundries in terms of flexibility and the minimum efficient scale of production runs.

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 database on technology alliances (Duysters and Hagedoorn, 1993). The selection included strategic alliances[10] 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 alliances. 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.

To measure technological capital, we used patent data from the U.S. Patent Office for all companies involved in the design and production of ASICs, also those based outside the US[11]. Working with U.S. patents - the largest 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 are a good proxy for companies' worldwide innovative performance[12].

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10. 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.

11 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'.

12 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, the distribution of the ASIC-sales across the three segments, R&D-intensity on the corporate level and total sales of these companies. 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 size of a company's technological capital. Technological capital is traditionally operationalized by patents granted to an innovating company. However, patents are not equal in value. Some patents refer to basic knowledge at the core of a technology, while others are merely of incremental value. The technological importance of innovations can thus be measured with patent citations (Albert *et al.*, 1991; Narin *et al.*, 1987). Therefore, the value of patents can be incorporated in our dependent variable by weighting the patents by the number of received citations. In order to correct for right-hand censoring we estimated the number of citations patents would receive over their life-span, based on the number of citations they received with the help of Hall *et al.*'s (2001) simulated cumulative lag distribution tables, using months rather than years. The NBER citations database was used for citation-information (Hall *et al.*, 2001). Thereafter we used a nonlinear weighting scheme, assuming the marginal informational content increases with the number of citations. Trajtenberg (1990) provides a weighting model for this. The time the company applied for the patent was used rather than the year when it was granted to the firm because a patent application is a signal that a company has developed a technological innovation. The dependent variable thus measures the number of patents that a company applied for in a particular year weighted by their received citations[13].

Independent variables

The first 5 hypotheses suggest a relationship between a firm's prior technological capital, 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.

Cumulative technological capital is calculated as the number of ASIC-related patents that an ASIC-producer obtained in the previous four years. Patents granted to a company are used to measure in an indirect way the technological competence of a company (Narin *et al.*, 1987). Studies about R&D depreciation (Griliches, 1979, 1984) suggests that knowledge capital depreciates sharply, losing most of its economic value within 5 years. A moving window of 4 to 5 years is therefore 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). In this paper we use the cumulated patents obtained by a firm during the 4 years previous to the year of observation 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 any of these particular time windows.

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[14]. Second, some authors weigh each type

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13 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 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.

14 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

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[15]. 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 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 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.

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to non-equity alliances which imply only moderate levels of organizational commitment (although stronger than arms' length licensing agreements).

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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		

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. In order to prevent a truncation bias in this weighting procedure we used the patent citations of the first five years after the patent was applied for only. This way, older patents were treated similarly to newer patents.

Novel technologies are measured by the degree to which a company experiments with technologies this firm did not use before (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. 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 more than one other patent[16].

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

[16] We choose to proxy pioneering technologies in this way because there were only a few patents

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. 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 rejuvenating or reinforcing their technological capital. This, in turn, requires a high rate of innovation. Finally, innovation output is a function of contemporary and lagged flow of the firms' annual R&D expenditures (Pakes and Griliches, 1984; Hall, *et al.*; Griliches, 1984, 1986). Since, there is a high correlation between sales and R&D expenditures (corr. = 0.96) we added R&D-intensity as a control. We expect that higher R&D-intensity will lead to higher patenting rate when controlling for size of the company.

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 - i.e. the weighted number of patents a firm filed for in a particular year. A Poisson regression approach provides a natural baseline model for such data (Hausman *et al.*, 1984; Henderson and Cockburn, 1996).

A Poisson regression assumes that the mean and variance of the event count are equal. However, for pooled cross-section count data this assumption is likely to be violated, since it is well know that count data suffer from overdispersion (i.e. the variance exceeds the mean). This overdispersion is particularly relevant in the case of

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in the sample that did not cite any other patent.

unobserved heterogeneity, i.e. the possibility that identical firms on the measured characteristics are still different on unmeasured characteristics[17]. 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.

In this case, the negative binomial model is more adequate. This model is highly related to the Poisson model and has the advantage over the latter that it allows for a different mean and variance. 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 negative binomial regression (Hausman *et al.*, 1984)[18].

Including the sum of patents that a firm has filed for in the last five years (moving window approach) as an additional variable is a common method of controlling for unobserved heterogeneity (Heckman and Borjas, 1980). A firm's history in filing for the two types of patents is an instrumental variable that helps to partial out the unobserved differences across companies. Furthermore, part of the heterogeneity between the subsectors, country of origin or years can be captured by including dummy variables in the model. First, the propensity to patent may be partly determined by the nationality and/or the sector of the companies. 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.

RESULTS

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

[17] 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.

[18] In particular, we assumed that the overdispersion parameter is drawn from a beta distribution.

Model 1 in table 4 functions as a baseline model and includes the three types of dummy variables (the coefficients for the 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 a control variable for unobserved heterogeneity. Firm size (corporate sales) has a positive and significant effect on the rate of innovation: this suggests that large companies are technologically and financially better equipped to innovate in the ASIC technology field. 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 their competitive advantage. Captive producers have a higher patent citation rate but the coefficient is only weakly significant in the following models in table 4. ASIC market growth - which can be considered as a proxy for the technology maturity - has no impact on the patent citation rate. Patents of European based companies are less cited than those of US-based or Asian companies. Finally, the significant coefficients of different industry segments indicate that the patent citation rate is not homogenous for the whole ASIC market.

Model 2 in table 4 adds the existing technological capital as an exploratory variable to the model. The existing technological capital of a company has a positive and highly significant effect on its innovative performance. An increase of one percent in the prior technological capital of a company leads to an increase in the patent citation rate of 5.4%. This supports the first hypothesis: companies that have an extensive technological capital get relatively more patent citations than other companies[19].

Model 3 includes the technology alliances formed by each company during the last five years. We also included the squared term because the second hypothesis suggests an inverted-U shaped relationship between the patent citation rate and the social capital of a company. The findings strongly support this hypothesis: the negative sign for the squared term indicates that there are decreasing returns to scale and that at some point there is a level of social capital beyond which companies are at risk to be overembedded. Model 3 also adds the interaction term between ‘social capital’ and

19 Negative binomial 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.

‘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.

In order to correctly understand the joint effect of social capital and technological capital on the innovative performance of firms, we first need to look at the partial effects of both types of capital on the innovative performance (i.e. multiplier of the patent citation rate)[20]. Technological capital moderates the relationship between social capital and innovative performance. This basically has two consequences. First, a larger amount of 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 patent citation rate.

Similarly, social capital moderates the impact of prior technological capital on the rate of innovation of a company. The effect of priori technological capital on the patent citation rate is positive for companies that did not establish a network of alliances. The positive effect gradually drops the stronger the company is embedded in its alliances network.

The total impact of both types of capital on the rate of innovation is visualized in figure 4:

Insert here figure 4

The graph compares the innovation performance 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. In order to avoid the effect of a few outliers we omitted five observations with the highest values for prior technological and social

20 The partial effect of the prior technical capital (TC) in Table 4, Model 3 is exp[TC*(0.0591-0.0015*SC)], where SC is the social capital. The partial effect of social capital is exp[SC*(0.1474-0.0023*SC-0.0015*TC)].

capital. The resulting plane in figure 4 is restricted to firms with social capital smaller than 30 ‘weighted’ alliances and technological capital smaller than 34 patents.

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: for each level of technological capital companies on the left (right) of that ‘curve’ can improve their innovation performance 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 prior patent portfolio the optimal number of ‘weighted’ alliances is 32. This number is reduced to 21 alliances when the company has a prior technological capital of 20 patents. Firms may over-invest in social capital as has been argued in the literature (Kogut *et al.*, 1992; Harrigan, 1985): there exists an area in figure where the effect of social capital on innovative performance is negative. For companies with no prior patents this area starts at high levels of embeddedness (32 ‘weighted’ alliances) but this threshold decreases with increasing levels of technological capital of a company[21].

Companies can improve their innovative performance by investing in social or/and technological capital when the size of their existing internal technological capabilities and social network is small. Hence, companies that have low levels of technological capital and social capital can improve their innovative performance by investing in both types of capital. 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. Extending a company’s patent portfolio when it is already extensive[22] improves the innovation performance – at least for the companies in the sample – but its impact shrinks the larger the existing patent portfolio. In theory it is possible that the effect of technological capital on the innovative performance is negative if social capital is larger than 39 ‘weighted’ alliances – and thus beyond the maximal value for that variable (see table 2).

[21] Only a few outliers in our sample have a social capital that exceeds this threshold.

Second, the plane in figure 4 provides no clear evidence for hypothesis 4. Although the interaction term is negative, its impact is too small to end up with two local optimal points reflecting two strategies that could coexist in the same industry: one that is based on relatively high levels of social capital combined with low levels of technological capital and the other one where strong internal technological capabilities are combined with a limited set of alliances. Figure 4 on the contrary shows that larger patent portfolios always enhance the innovative performance of a company. Consequently, ASIC-producers with extended patent stocks and a moderate number of partners have the highest innovative performance[23].

Third, a closer inspection of the plane in figure 4 shows that companies with a broad existing patent portfolio benefit much more from collaborating with a few alliance partners than their counterparts that have a small patent portfolio. The ‘absorptive capacity’ of the former facilitates the generation of joint knowledge with their alliance partners. As a result, the limited number of partners they need to reach the optimal innovative performance might be explained by their strong absorptive capacity that is the result of previous investments in technology. Similarly, the effect of prior technological capital on the technological performance of a company increases progressively with higher levels of social capital up to a level of 14 to 20 alliances[24]. In short, we have evidence that at small levels of social en technological capital companies can increase technological performance more than proportionately with increasing levels of these two types of capital. Beyond the threshold of 14-20 alliances the impact of prior technological capital is decreasing again and even becomes negative after (the theoretical level of) 39 alliances.

Model 4 introduces the innovative performance of the alliance partners. The coefficient is positive but not statistically significant indicating that the patent citation

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22 A closer inspection of figure 6 shows that the impact becomes smaller once social capital is larger than 20 ‘weighted’ alliances for low levels of prior technological capital and larger than 14 alliances for the highest levels of existing technological capital represented in figure 6.

23 Hypothesis 4 is corroborated by the results, when a simple count of the patents is used as dependent variable. The difference in results is an indication that companies with a large patent stocks have relatively more important patents that are more frequently cited than companies that have a small technological capital.

24 This threshold depends in its turn on the level of prior technological capital.

rate of ASIC-producers is on average not enhanced by the technological strengths of their alliance partners. As a result, we have no empirical evidence for hypothesis 5.

Model 5 tests the two final hypotheses and offers support for both of them. Firms experimenting with novel technologies are more likely to have a higher patent citation rate. 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: the negative and significant coefficient for the squared term of novel technologies indicates that experimentation with novel technologies 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. 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 40.1 percent increase in a company's rate of innovation[25].

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 although the coefficient is only weakly significant. A one-standard deviation increase in the experimentation of pioneering technologies leads to a 9.8 percent (=exp[0.2754*0.34]) 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

[25] The partial effect of the novel technologies (NT) in Model 5 is exp[NT*(0.3020 -0.0304*NT)]. For an average company this implies a rate of innovation increase of 26.8 percent (exp[0.86*(0.3020-0.0304*0.86)]). For a company that is highly involved in experimenting with novel technologies (one-standard deviation above the mean) this increase is 66.9 percent

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 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 prior technology capabilities of a company or an extension of the alliance portfolio on its innovation performance 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 progressively 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 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. Companies with extended technology alliance networks benefit from a strong patent portfolio but the marginal benefits from increased patent stock becomes smaller the larger their social 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.

(exp[2.17(0.3020-0.0304*2.17]). The highest possible value for the partial effect (111.6 percent)

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 and 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.

is reached for companies having experimented with 4.85 novel technologies.

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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.

Table 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 partnersPositive	
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 more than one other patent	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	

Table 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	17
1	Cumulative patents$_{t-1}$	2.67	5.85	0	70																	
2	Cumulative technology alliances$_{t-1}$	4.05	6.90	0	38	0.33																
3	Innovative performance of alliance partners	46.91	129.48	0	1251	0.30	0.39															
4	Novel technologies$_{t-1}$	0.86	1.31	0	11	0.43	0.33	0.37														
5	Pioneering technologies$_{t-1}$	0.08	0.34	0	3	-0.02	0.04	0.01	0.11													
6	R&D intensity	0.12	0.06	0.04	0.41	-0.10	-0.14	-0.06	-0.08	-0.01												
7	Log ASIC sales$_{t-1}$	2.95	2.03	-0.69	7.43	0.47	0.43	0.24	0.30	0.04	-0.09											
8	Firm size (log sales)$_{t-1}$	6.20	3.30	-0.92	12.60	0.31	0.40	0.21	0.24	0.06	-0.59	0.52										
9	ASIC market growth$_{t-1}$	0.14	0.03	0.10	0.21	-0.02	0.09	0.00	-0.05	0.03	-0.01	-0.06	-0.02									
10	Firm is a captive producer	0.11	0.31	0	1	-0.04	0.01	-0.01	-0.02	0.01	-0.20	-0.28	0.20	-0.01								
11	Firm is Asian	0.22	0.42	0	1	0.13	0.00	0.00	0.07	0.07	-0.43	0.14	0.40	0.00	-0.10							
12	Firm is European	0.17	0.38	0	1	-0.12	0.15	0.09	-0.11	-0.04	-0.04	-0.01	0.10	0.01	0.12	-0.25						
13	Firm is GA-producer	0.12	0.32	0	1	-0.13	-0.16	-0.10	-0.12	-0.03	0.10	-0.07	-0.13	0.00	-0.02	-0.12	-0.14					
14	Firm is SC-producer	0.18	0.39	0	1	-0.15	-0.15	-0.07	-0.09	-0.04	0.15	-0.12	-0.20	-0.03	0.00	-0.21	0.14	-0.17				
15	Firm is PLD-producer	0.07	0.25	0	1	0.24	-0.01	0.07	0.15	-0.02	0.25	0.16	-0.13	-0.02	-0.09	-0.14	-0.12	-0.10	-0.13			
16	Firm is GA and PLD producer	0.01	0.09	0	1	0.03	0.09	0.02	0.04	-0.01	0.06	0.07	0.00	0.04	-0.03	-0.05	-0.04	-0.03	-0.04	-0.02		
17	Firm is GA and SC producer	0.30	0.46	0	1	0.14	0.07	0.07	0.11	0.10	-0.24	0.44	0.38	0.00	-0.12	0.35	-0.03	-0.24	-0.31	-0.17	-0.06	
18	Firm is SC and PLD producer	0.01	0.08	0	1	-0.03	0.17	-0.02	0.04	-0.01	0.00	0.04	0.06	-0.01	-0.03	-0.05	-0.04	-0.03	-0.04	-0.02	-0.01	-0.06

N = 830 observations

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

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Cumulative patents$_{t-1}$		0.0526***	0.0591***	0.0609***	0.0537***
		(0.0065)	(0.0077)	(0.0079)	(0.0082)
Cumulative technology			0.1474***	0.1436***	0.1345***
alliances$_{t-1}$			(0.0236)	(0.0238)	(0.0236)
(Cumulative technology			-0.0023***	-0.0022***	-0.0023***
alliances$_{t-1}$)^2			(0.0008)	(0.0008)	(0.0008)
(Cum. technology alliances $_{t-1}$)			-0.0015***	-0.0017***	-0.0018***
* (cum. patents $_{t-1}$)			(0.0004)	(0.0005)	(0.0005)
Innovative performance of				0.0004	
alliance partners				(0.0004)	
Novel					0.3020***
technologies$_{t-1}$					(0.0995)
(Novel					-0.0304*
technologies$_{t-1}$)^2					(0.0183)
Pioneering					0.2754**
technologies$_{t-1}$					(0.1163)
R&D intensity	3.14166**	3.7589**	3.1553*	3.2673**	3.4754**
	(1.6037)	(1.5581)	(1.6378)	(1.6447)	(1.6816)
Log ASIC sales$_{t-1}$	0.3813***	0.2786***	0.1504***	0.1586***	0.1581***
	(0.0504)	(0.0507)	(0.0536)	(0.0543)	(0.0540)
Firm size	0.2323***	0.2184***	0.1256***	0.1250***	0.1212***
(log sales)$_{t-1}$	(0.0450)	(0.0438)	(0.0435)	(0.0436)	(0.0440)
ASIC market growth$_{t-1}$	10.2939	11.2207	5.1625	5.341	10.7451
	(12.6046)	(12.4985)	(11.2919)	(11.3558)	(12.0914)
Firm is a captive	0.5592**	0.4449*	0.4625*	0.4767*	0.4862*
producer	(0.2618)	(0.2568)	(0.2628)	(0.2638)	(0.2637)
Firm is Asian	0.2721	0.2225	0.5582***	0.5795***	0.5948***
	(0.1945)	(0.1906)	(0.2006)	(0.2018)	(0.1995)
Firm is European	-0.7181***	-0.6197***	-0.8246***	-0.8349***	-0.7924***
	(0.2341)	(0.2295)	(0.2348)	(0.2355)	(0.2392)
Firm is GA-producer	-0.6963**	-0.5963**	-0.1918	-0.2067	-0.1661
	(0.2879)	(0.2833)	(0.2935)	(0.2935)	(0.2893)
Firm is SC-producer	-1.0775***	-0.9512***	-0.7136***	-0.7302***	-0.6835**
	(0.2729)	(0.2692)	(0.2737)	(0.2738)	(0.2725)
Firm is PLD-producer	0.5550**	0.3121	0.6117**	0.5418*	0.4316
	(0.2739)	(0.2765)	(0.3013)	(0.3072)	(0.3037)
Firm is GA and SC	-0.5111***	-0.3441**	-0.1247	-0.1598	-0.2576
producer	(0.1688)	(0.1637)	(0.1790)	(0.1812)	(0.1784)
Firm is GA and PLD	1.2699***	1.3787***	1.1467**	1.0968*	1.1277**
producer	(0.4883)	(0.4639)	(0.4807)	(0.4841)	(0.4695)
Firm is SC and PLD	-0.8289	-0.6303	-1.3176*	-1.2787*	-1.3258*
producer	(0.7507)	(0.7456)	(0.7463)	(0.7475)	(0.7497)
Year dummy variables included					
Constant	-8.0146***	-7.8331***	-6.6201***	-6.6692***	-7.7684***
	(2.4387)	(2.4169)	(2.1878)	(2.1996)	(2.3423)
Number of firms	99	99	99	99	99
Number of firms-years	830	830	830	830	830
Log-likelihood	-2109.3	-2084.5	-2051.9	-2051.2	-2042.8
Likelihood-ratio test panel vs. pooled (χ^2)	63.52***	43.88***	45.59***	46.77***	44.34***

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$
'Year dummy variable'-coefficients are not reported in the table.
The models use a random effects negative binomial regression. The sample is an unbalanced panel with 99 ASIC producers and 830 firm-years (units of observation).

Figure 1: The ASIC technology field

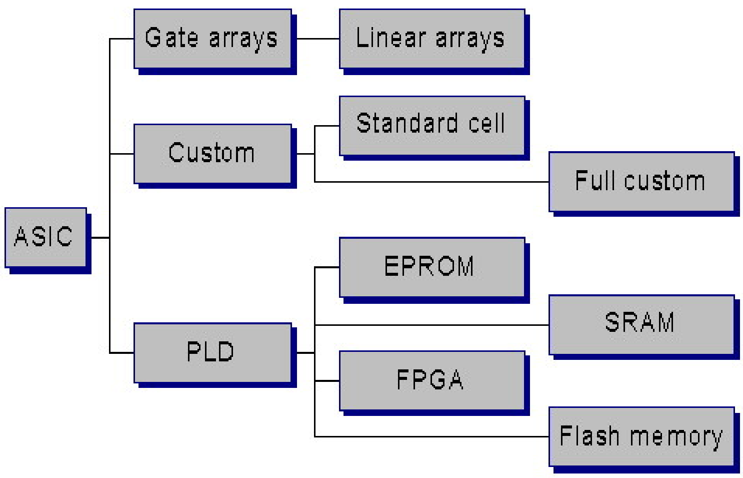


Figure 2: The segments in the ASIC technology field

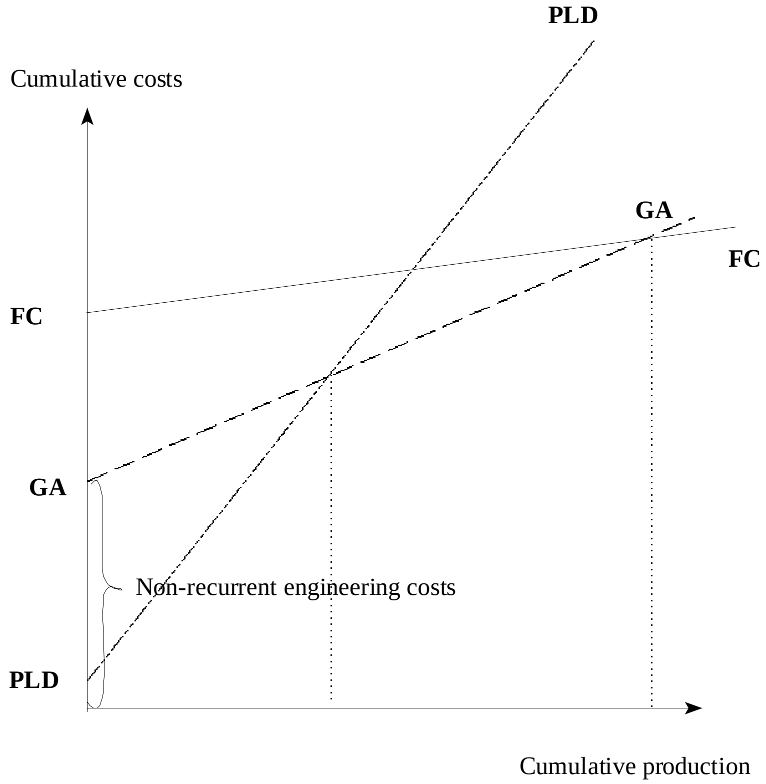


Figure 3: The ASIC technology field

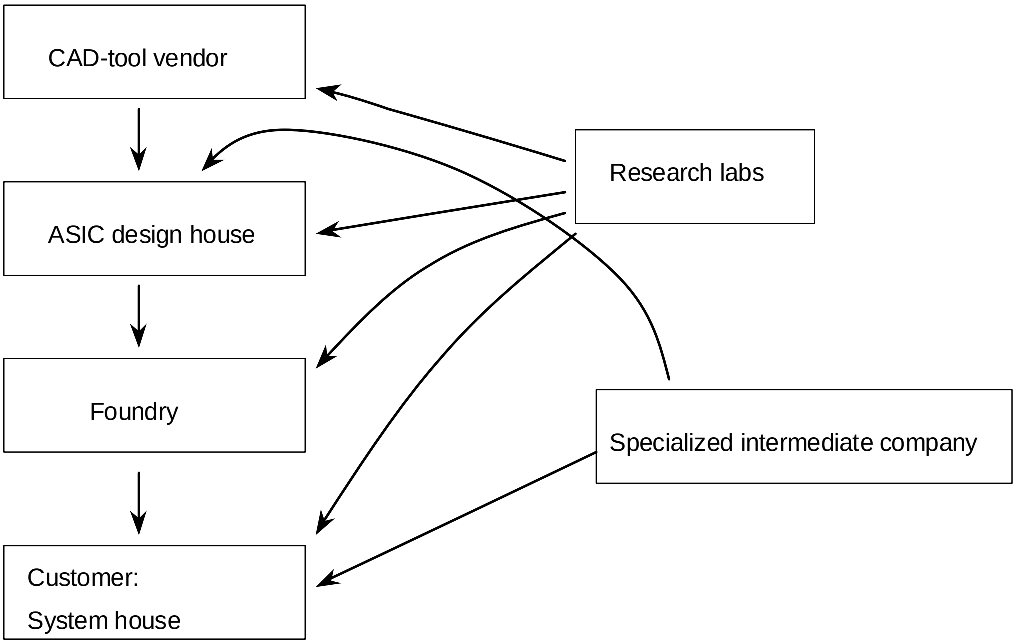
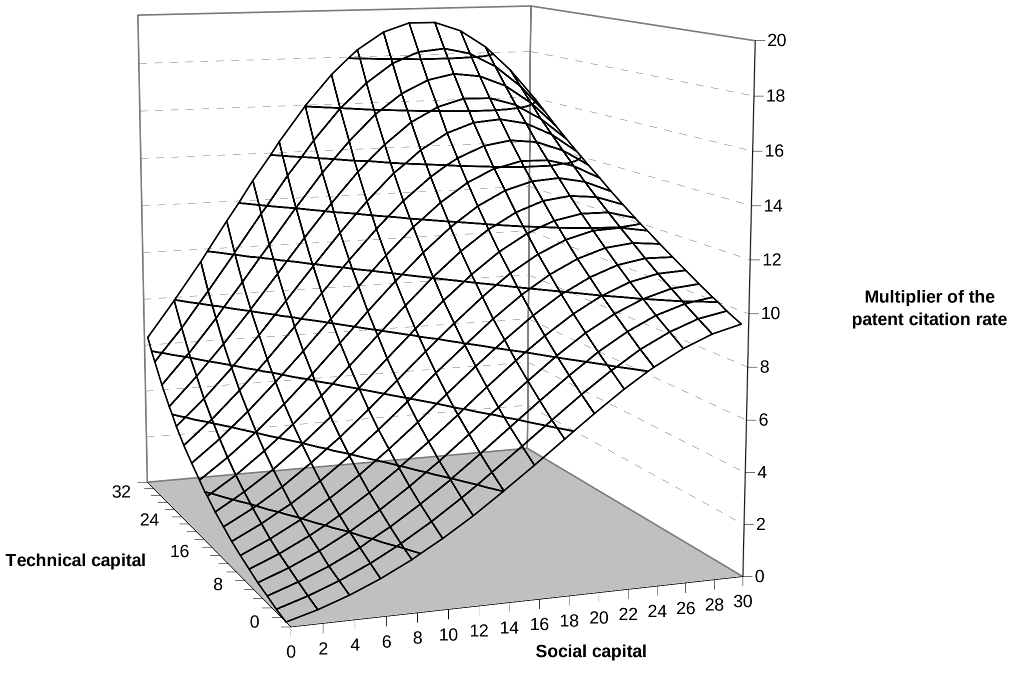


Figure 4: Impact of social and technical capital on the patent citation rate



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