Boundary Spanning Inventors and Firm Innovation: How Spillovers from Science are not Free[♣]

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Abstract

The paper studies the effect of "boundary spanning inventors" – inventors that cross organizational boundaries and bridge between scientific and technology communities – as a mechanism through which firms connect to and appropriate returns from science. We examine the case of IMEC, a world leading research institute in the area of nano-technology, with a mission to bridge the gap between fundamental research at universities and R&D in the industry. We find strong evidence that linking to IMEC has provided partner firms with tangible benefits such as more valuable technology outcomes that are developed faster by these partner firms. Boundary spanning inventors increase the chance of developing high quality technologies faster, but need to be embedded within a broader partner relationship for this network to produce tangible results.

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1. Introduction

An important and recurrent concern in economics and management has been to understand to what extent scientific knowledge influences technological progress and ultimately economic growth. More recent research suggests that the links to basic research and scientific knowledge by industrial firms have dramatically increased in the last decade and that firms today manifest a diversity of links. In spite of these growing connections to science our understanding of the variety and distribution of these links and how they affect industrial innovation remains unclear.

In this paper we examine the effect of links to science on firm's applied research productivity. We contribute to the literature in several ways. First, we examine several potential effects of science links, ranging from effects on the value and quality of technologies developed over building cumulativeness of research to establishing technology lead time. Second, we examine various linking mechanisms and their possible complementarities. Beyond joining of cooperative programs, we also look at the mobility of boundary spanning inventors. Third, while controlling for both inventor and organizational level effects, we examine the effects of links to science at the invention level. Most research has used a knowledge production function at the organization level. However, such an approach aggregates many of the effects and, we believe, loses some of the important effects of science at the invention level. Firms that actively link with science will have a wide portfolio of innovative projects. It is important to examine the effect of the science link on the projects that directly lead to commercial applications and are comparable to the projects of firms that have no direct link to science.

The links to science that we examine focus on the links through an intermediary research organization. We study a program set up by IMEC, a world class research organization in micro-electronics and semiconductors with the expressed objective to bridge the gap between fundamental research done at universities and R&D in the industry. IMEC runs an industrial partner program where firms can sign up to specific research programs in their area of interest. Partners send researchers to participate in the research program at IMEC where they interact with researchers of IMEC and other partners involved in the program. However, the researchers formally remain part of their original organization and only physically move between locations to interact with science and engage in applied research. IMEC negotiates an elaborate IP agreement with its partners. This allows us to track the effects of affiliation to this the program as well as the actual mobility of people and ideas, through patent information.

The analysis involves comparing patents at different levels. Patents of firms that are affiliated with IMEC are compared to patents of firms not involved with such an intermediary research organization. This allows us to trace the effect of affiliation to an intermediary research organization. In addition, we compare patents of boundary spanning inventors of affiliated firms that have been participating in research programs at the intermediary research organization versus patents of inventors who did not participate is such a program. This allows us to trace the effect of cross-institutional mobility of researchers.

We find that firms linked to science and applied research in semiconductors through IMEC and use boundary spanning inventors develop high quality innovations in the technology domain where IMEC operates. Partners continue to build internally on these technologies and cite IMEC related technologies faster, improving appropriation of returns in this fast paced environment. Being a partner of IMEC is important for developing higher quality inventions and clearly affects the appropriation strategy of these firms which use their inventors' experience and the technologies they created as a bridge to the next generation of commercial technologies. Boundary spanning inventors are an important link when used in combination with affiliation. The inventors visiting the research center seem to play a key role in timely anticipating future technology roadmaps and reducing lead time in developing these future commercial technologies.

In the following section we discuss the literature on industry science links. Section 3 develops our hypotheses, while Section 4 discusses the empirical setting of IMEC. Section 5 elaborates on our data development and methods. Section 6 presents our results, while Section 7 concludes with some caveats and directions for further research.

2. Literature Review

The interrelation between science and firm-level innovation outcomes is covered in a diverse literature in Economics and Management. While the economics literature mainly explores the effects of science on innovative performance, it provides little explanation about the process through which science affects innovation. The management literature has tried to open the black box inside organizations on how science links effectively translate into improved (innovative) performance.

Any explanation of why firms engage with science needs to argue that ultimately science enhances firms' innovative performance. Several explanations as to the exact mechanisms for enhancing applied research productivity have been suggested (Nelson; 1959; Evenson and Kislev, 1976; Cassiman, Perez-Castrillo and Veugelers, 2002). As science provides a codified form of problem-solving, it increases the efficiency of private research (Arrow, 1962). In addition, science serves as a map for technological landscapes guiding private research in the direction of most promising technological venues avoiding thereby wasteful experimentation (Fleming and Sorenson, 2004). Probably the most discussed argument of how actively engaging in science might increase applied research productivity is the fact that this link to science leads to a better identification, absorption and integration of external (public) knowledge (Cohen and Levinthal, 1989; Gambardella, 1995; Cockburn and Henderson, 1998; Cassiman and Veugelers, 2006). Faster identification, absorption and integration of external knowledge in turn leads to increased productivity of the applied research process, resulting faster into new technologies (Fabrizio, 2009; Cassiman et al., 2008).

Scientific curiosity can create diversity in approaches and improve innovation outcomes (Page, 2007). A better and more fundamental understanding of the technology landscape encourages non-local search for improving technologies as opposed to local search, leading to more diverse research projects being explored. More basic knowledge can simultaneously fertilize different research projects. At the same time, scientifically active firms can be expected to generate “unexpected” outcomes, which in turn improves the productivity of applied R&D and as a consequence the productivity of the innovation process (Sobrero and Roberts, 2001; Cassiman and Valentini, 2009; Aghion et al., 2009).

Finally, rather than affecting the output of the innovation process, Stern (2004) argues that science active firms might affect the inputs of the innovation process. By setting up a science friendly environment, the firm attracts researchers willing to accept a lower salary in return for the freedom to publish. These researchers are twofold valued: they do not only imply important labor costs reductions for the firm, but also they constitute the “bridge” with the scientific or academic world. Scientific advances and technological advances are driven by different selection logics and developed in different institutional environments (Gittelman and Kogut, 2003). Therefore, crossing organizational boundaries seems an important requirement to access good scientific knowledge. Mobile inventors or inventors that can link to science are probably the most efficient bridge between these two environments. However, little work has explicitly examined this boundary spanning role of these inventors bridging scientific and technology communities (Breschi and Catalini, 2010).

Mostly focused at the *firm-level of analysis*, the empirical literature has taken a stab at assessing the impact of science links on firm performance. In spite of the many paybacks to be anticipated, the adoption of science remains limited to a restricted set of firms, and there is a wide heterogeneity in effects from science. Most empirical evidence shows that adoption of science is indeed not costless. It is highly conditional on absorptive capacity (Cohen and Levinthal, 1989; Kamien and Zang, 2000) and adoption of new organizational practices (Gambardella, 1995; Cockburn *et al*, 1999).

Probably the largest group of empirical papers have estimated a patent production function examining the effect of partnerships with universities on firm performance (e.g. Audretsch and Stephan, 1996; Zucker *et al* 1998; Cockburn and Henderson, 1998; Brandstetter and Sakakibara, 1998). The eminence of cooperation with universities as industry science link mechanism is reminiscent of the importance of crossing institutional boundaries for effective knowledge transfers between scientific and technology communities (Kogut and Zander, 1992; Rosenkopf and

Nerkar, 2001). The empirical evidence from these studies support the complementary effect of cooperation on internal R&D (Adams, 2000), and find a positive effect on innovation productivity and sales (Belderbos *et al*, 2004; Belderbos et al, 2006).

The work by Cockburn and Henderson (1998) has shown that also direct involvement into science matters. Using data on co-authorship of scientific papers for a sample of pharmaceutical firms, they show that firms connected to science through co-publications show a higher performance in drug discovery. Also Cassiman, Veugelers and Zuniga (2008) find that firms with scientific (co-)publications generate more important "applied" patents. Ties with academic star scientists, either through co-publications or board positions, are another industry science link found, especially in biotech, to lead to more technology (Henderson and Cockburn, 1996; Zucker *et al*, 2002; Cockburn and Henderson, 1998); more "important" patents: i.e. international patents (Henderson and Cockburn, 1994); and higher average of quality adjusted patenting (Zucker and Darby, 2001; Zucker *et al*, 2002).

At the *invention* (i.e. patent) *level*, mainly the effect of the citation of scientific literature or the involvement of an academic researcher has been examined. Patents with references to science are found to be more important applied technologies (Cassiman, Veugelers and Zuniga, 2008), and to generate more economic value for pharmaceutical and chemical patents, but not in other technical fields (Harhoff et al., 2003). Fleming and Sorenson (2004) show that having a "scientific" reference matters for technological impact of patents but that the benefits of using science depend upon the difficulty of the inventive problem being addressed: science only appears as beneficial when researchers work with highly interdependent – or coupled – knowledge pieces, which makes probability of discovery more uncertain. However, no significant effect of scientific references is found to explain patent opposition in European patents (Harhoff and Reitzig, 2004). The involvement of an academic inventor in the invention team is found to lead to more valuable patents, which is in line with having a boundary spanning inventor on the team (Czarnitzki et al., 2008).

At the *inventor* level, those inventors co-publishing with universities are found to generate patents that exploit more prominently (citations to) science, confirming their boundary spanning role. These inventors also produce patents with shorter lags between existing inventions and new firm inventions in the pharmaceutical industry (Fabrizio, 2004). More mobile researchers are found to have better access to resources and networks (Cañibano, Otamendi and Andujar, 2008) and consequently have a higher innovative performance (Hoisl, 2007; Palomeras, 2010). Reminiscent of the importance of mobility of researchers as mechanism to transfer information across organizations, improved performance is also found for the receiver firm (Song, Almeida and Wu, 2003; Rosenkopf and Almeida, 2003; Singh, 2008), as well as for the sender firm (Corredoira and Rosenkopf, 2010; Oettl and Agrawal, 2008).

While the firm level empirical analyses find a positive relation between scientific activity of the firm and innovation outcomes, these analyses pay little attention to the actual micro-level mechanisms that link scientific activity to innovation performance. At the same time the invention and inventor level analyses do not clearly specify and control for organization level connections of the firms and limit themselves to inventor networks without superimposing organizational structures that affect the incentives of these inventors to develop, communicate and appropriate returns to these scientific research activities. In what follows we investigate which links matter and how by carefully specifying what we know in a particular case. Our analyses are probably most closely related to Ziedonis & Ziedonis (2005) where they examine the specific case of SEMATECH. Given the particular features of our research setting we are able to delve deeper into these links and their effects as we discuss below.

3. The effects of Linking with Science: our Predictions

The literature provides ample evidence showing that firms with links to science on average might expect higher innovative performance. But unfortunately we still know little about how exactly science links affect firm performance and which organizational forms are important for this linking. How can firms take more advantage of scientific research in their applied research? How should they organize to take advantage of science?

3.1. On mechanisms to link to science

Based on the literature, we hypothesize that the spanning of organizational boundaries seems more effective to access good scientific knowledge and generate technological advances. Through the mobility of the right people the frictions in this knowledge transfer process across organizational boundaries can be minimized. Especially, because of the tacitness and complexity of know-how underlying leading edge research, researcher interaction and mobility does play an essential role. We therefore expect links involving mobility of researchers, i.e. boundary spanning inventors, to make organizational boundary-crossing more effective. We will distinguish between these pure boundary spanning inventor links relative to more structured organization level partner links.

3.2. On effects from science links

Interactions between science and industry should stimulate the average quality of the applied technologies developed by interacting firms. In addition, we would expect firms to take advantage of knowledge flows that have been generated through linking across organizational boundaries with science by building on these knowledge flows through the internal development of new technologies. This is particularly important for technologies that are cumulative in nature. Not only does the link to science allow the firms to develop better technologies, as argued, it also allows these firms to move faster in technology space and stake out important technologies that they and others might build on.

As a consequence, effects from industry science links and boundary spanning inventors in particular should be reflected in the value and quality of the developed technologies by the firms generating inventions with high potential. At the same time, they affect the cumulativeness of their research efforts, and, the speed at which these organizations move in technology space. Given the improved knowledge flows across organizational boundaries through boundary spanning inventors, we might also expect firms to build more and faster on the opportunities offered by these knowledge flows.

4. Research Setting: nano-electronics and IMEC

In this analysis we focus on the micro-electronics industry and analyze the effect of links with IMEC – the Interuniversity Microelectronics Center – as an intermediary between science and industry. We examine the effects of participating in its Industrial Affiliation Program (IIAP), which allows researchers from participating companies to conduct research at the IMEC laboratories.

4.1. Industry-science links in the micro-electronics industry

The micro-electronics industry is an interesting environment for testing effects of links with science. First, academic research is often at the forefront of breakthroughs in nano-electronics, and for this reason companies are seeking to cooperate with universities and research institutes to tap into emerging scientific opportunities as soon as possible. Academics are at the forefront of discoveries within their field, but the challenge remains to bridge the large gap between the application-oriented needs of the industry and the results from scientific research performed at universities and research institutes.

Second, the semiconductor business is a knowledge-intensive industry whereby leading-edge technological knowledge is mostly tacit in nature. Knowledge sharing via researcher interaction and mobility between firms and research organizations is shown to be the crucial mechanism to bridge this gap between scientific and technology communities (Meyer-Krahmer and Schmoch, 1998). Knowledge creation in the semiconductor business is furthermore characterized by cumulativeness (Hall and Ziedonis, 2001). At the same time, time-to-market has increasingly become a major differentiator as a result of fierce competitive dynamics and the shortening of product-life-cycles. In addition, patenting is a standard practice in this industry (Hall and Ziedonis, 2001) and as a result, patents provide a clear window on the technology and innovation activity in the industry.

4.2. IMEC as industry-science link

We conduct our study based on IMEC a world-leading independent research institute in the area of nano-electronics and nano-technology. In 1982, IMEC was founded by the Flemish government. Its mission was to bridge the gap between fundamental research at universities and R&D in the industry. The centre was built on the academic reputation and prominence of the ESAT laboratory of the University of Leuven. The centre's commitment to the scientific community is nicely illustrated by the close collaboration with world-class universities, by the numerous conference participations and publications by its researchers and by the presence of several doctoral researchers at its laboratories.[1]

At the same time, IMEC is closely linked with industry. The board of directors includes delegates of the industry who stipulate the centre's strategic roadmap focused on pre-competitive application-oriented technologies three to ten years ahead of industrial needs. IMEC was able to attract top industry leaders such as Intel, Samsung, Texas instruments, Micron, NXP, Hynix, Elpida, Infineon, Panasonic, TSMC, Sony, Qualcomm and ST Microelectronics as partners. Together with IBM in Albany, IMEC in Leuven has become one of the two most flourishing centers for nano-electronic research. IMEC possesses a unique pool of competences in a diversity of technological fields. It possesses a rare combination of know how in chip design, packaging and production. Its unique business model aims at stimulating the mobility of researchers in order to facilitate cross-fertilization of ideas among all participating scientific and industrial researchers.

4.3. IMEC Industrial Affiliation Program (IIAP)

IMEC's Industrial Affiliation Program (IIAP) is designed to create an innovation model in which affiliated companies share costs, risks, human resources and intellectual property while engaging in collaborative R&D on generic technologies.

1 In 2010, IMEC was collaborating with approximately 200 universities worldwide in its core CMOS (Complementary Metal Oxide Semiconductor) division only and hosted 194 visiting PhD students at its research facilities. IMEC's own researchers, around 1000, published more than 1,750 scientific articles in 2009.

Guest researchers, including academic and industrial researchers affiliated to one of its partners, are conducting research at the IMEC laboratories in close collaboration with other researchers. Besides IMEC's own research personnel (about 1000), more than 520 guest researchers with 60 different nationalities were conducting research at IMEC's laboratories in 2010, including 344 industrial researchers. Each partner firm sends some of its researchers to collaborate in the programs in which the firm participates.

Around 15 different industrial affiliation programs were running in 2010, of which a large majority in the Process Technology Unit. These programs are focused at solving production issues involved in the next generation of semiconductors.

4.4. IMEC's IPR-model

Crucial for its IIAP business model is an aligned IP-strategy so that all collaborating partners are able to build their own and unique IP-portfolio on top of shared IP. IMEC has elaborated an IP-strategy to stimulate this technology development and to limit blocking amongst its corporate partners (Van Helleputte, 2004).[2] The basic platform technologies are accessible to all its partners. These technologies, developed by IMEC or by IMEC in collaboration with partners, are still in a precompetitive phase and require additional R&D to be ready for final application. Corporate partners can build on these technologies to develop proprietary IP in line with their own commercial needs. All technology developed at the IMEC laboratories, in execution of dedicated IIAP-programs by academic or industrial researchers, is contractually co-owned by IMEC unless otherwise contractually stated.

[2] Johan Van Helleputte is the director for strategic development at IMEC.

IMEC's IPR-model classifies patents based on ownership. IMEC patents referring to background knowledge on semiconductor technologies are assigned exclusively to IMEC and labeled "R0". External partners in the IIAP gain access to it, as far as needed for the exploitation of the program foreground Information, via a non-exclusive and non-transferable license. These patents constitute the more fundamental technological knowledge base generated by IMEC in order to set up platform programs within particular strategic fields with the intention of attracting external partners. Technologies that are co-developed with companies in the context of IIAP projects, i.e. the collaborative industrial R&D projects conducted at IMEC's laboratories are labeled "R1". These patents are co-assigned to IMEC and the companies collaborating in R&D. A partner gets access to the generated IP within the technical domain as defined in its contract with IMEC. Technologies which result from proprietary research activities within IMEC, applying the generic "R1" results to the company specific setting are labeled "R2" and are assigned exclusively to the partner.

IMEC's business model and the corresponding IP-model are recognized worldwide as a successful medium to stimulate industry-science links, R&D collaboration and ultimately technology development in the industry. For our analysis, it allows to track the mobility of people and ideas around IMEC, as will be detailed in the next section.

5. Data and Methodology

5.1. Data and Sample

5.1.1. Sample Selection

Our dataset is constructed by collecting first all patent applications filed by IMEC between 1990 and 2005 which we retrieved from the Worldwide Patent Statistical Database (PatStat edition April 2008). From this sample of 578 patents,[3] we identified 531 unique inventors, i.e. inventors affiliated to IMEC or to one of its partners, including companies, universities or other research institutes. This set of patents was validated by IMEC.

Second, we retrieved all patents from IMEC affiliated inventors, i.e. inventors on an IMEC patent. All different name variants and corresponding person identification numbers of this set of inventors were retrieved using search keys to take into account different spellings. We collected 1863 patents mentioning at least one IMEC affiliated inventor. The use of detailed personnel data obtained from IMEC allows us to identify the affiliation of an inventor at a particular moment in time. We eliminated all IMEC employees at the time of patenting and name these remaining inventors "boundary spanning" inventors as they have been active in the generation of IP at IMEC at some point in their career.[4]

Third, we collected all patents citing the set of original patents with IMEC as an applicant. These patents share the same technological space as the IMEC patents and provide a reasonable control group for our selection of patents.

The final sample to analyze the effects of science links consists of 1,089 USPTO patents, 1,835 unique inventors and 87 companies.[5] Figure 1 provides a

[3] These patents include EPO, USPTO and PCT patent applications

[4] The match of inventor names was made based on matches of name, first name, initial and address. In the case of differences in addresses or names, we checked the technology field of the patent and the applicant name to determine a match. While this rigorous approach might lead to false negative matches (type I error), it minimizes/eliminates false positive matches (type II error). Given our objective to trace inventor interaction and mobility, this conservative approach seems most appropriate.

[5] The initial sample consists of 5,802 patents (825 IMEC patents, 1,038 patents from IMEC affiliated inventors and 3,939 other patents citing IMEC patents), 7,566 unique inventors and 1,348 unique applicants, including around 1,200 companies, 82 universities and 66 research centers. For the remainder of the analysis, we restrict attention to USPTO patents only (3,606) and subsequently eliminate patents (co)assigned to IMEC (302), patents not assigned to companies (488), patents from

visual description of the final sample construction. The sample can be divided between 221 company-owned patents which mention at least one boundary spanning IMEC affiliated researcher employed by the assignee company[6] as inventor and 868 company-owned patents without this inventor link but citing a patent (co)assigned to IMEC. Each group of patents can further be subdivided based on whether the applicant company is a partner collaborating in IMEC's industrial affiliate program. This results in 176 patents assigned to partner companies and mentioning a boundary spanning IMEC visiting researcher as inventor, 45 patents assigned to non-partner firms but having a boundary spanning inventor on the patent, 435 patents assigned to partner companies and citing IMEC patents and 433 patents assigned to non-partner companies but citing IMEC patents. This classification allows us to analyze the separate and combined effects of having organizational and individual links with science through IMEC.

Insert Figure 1 here

5.1.2. Classification of patents: invention-, inventor-, and organizational-level links with IMEC

To classify the patents we have exploited IMEC's basic IPR-model. We used the following procedure in line with IMEC's IP-model and defined the IMEC technologies as follows:

- R0 are patents exclusively assigned to IMEC or co-assigned to IMEC and universities or individuals,

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companies with less than 4 patents in our sample, patents which do not share the same technological space as the IMEC patents, for which we don't have all relevant characteristics or for which we don't have information on the affiliation of the IMEC visiting researcher (1,745).

[6] We obtained information on the affiliation of both payroll and non-payroll researchers from IMEC. This data, in combination with information from the internet, allowed us to make sure that an inventor is indeed employed by the assignee company. We eliminated all cases whereby no information is available on the affiliation.

- R1 are patents co-assigned to IMEC and affiliated "partner" companies

In addition, we define four new categories:

- BoundarySpanning-Affiliate patents are patents assigned to an IMEC affiliated partner organization and developed by a boundary spanning inventor, i.e. an inventor that has been active in the generation of IP at IMEC at some point in their career.
- Citing-Affiliate patents are patents assigned to affiliated partners citing R0-R1 patents, but without being developed by a boundary spanning inventor.
- BoundarySpanning-NonAffiliate patents are patents assigned to non-affiliate companies, but that have a boundary spanning inventor as an inventor on the patent.
- Citing-NonAffiliate patents are patents assigned to non-affiliated companies but citing R0 or R1 patents but without being developed by a boundary spanning inventor.

The classification of the patents according to this methodology allows us to estimate the impact of boundary spanning inventors and affiliate linkages with science at the invention (patent) level. The strongest link is a combination of boundary spanning inventor and organizational-level links, as is the case for BoundarySpanning-Affiliate patents. Patents that only have an organizational-level link with the research center are Citing-Affiliate patents, while BoundarySpanning-NonAffiliate patents are patents with only an inventor link to IMEC. These are most likely cases whereby a non-partner company hires away an affiliated or visiting researcher. Finally, Citing-NonAffiliate patents don't have any affiliated nor inventor link except for the fact that these patents cite an R0 or R1 and, hence, were developed in the same technology space. These are the ultimate control group to compare our various link-categories to. Note that in contrast with some of the literature, we do not consider a citation by a firm patent to IMEC as a genuine knowledge link. We use citations for identifying technology related patents.

Figure 2 below gives an overview of the classification of patents according to the links with science through IMEC.

Insert Figure 2 here

5.2. Measures for Innovation Quality, Cumulativeness of Research, and, Technology Lead Time

By classifying all patents according to boundary spanning inventor and/or affiliate links with IMEC, we estimate the impact of different links on various outcome dimensions.

5.2.1.1. Quality of Innovation

To evaluate the effect of linking to science through IMEC on the technological impact and the economic value of an organization's patents, we employ an indicator proposed in past studies on patent quality. The most used indicator of patent value and quality is the *number of forward citations* received from subsequent inventions. The number of forward citations a patent receives is related to its technological importance (Albert et al., 1991; Carpenter et al, 1993; Henderson et al., 1998; Jaffe et al., 2000), social value (Trajtenberg, 1990), private value (Harhoff et al, 1999; Hall et al., 2005), patent renewal (Harhoff et al, 1999) and patent opposition (Lanjouw and Schankerman, 1999). Research based on an inventor-targeted survey to estimate the economic value of European patents also reveals that although forward citations carry a lot of noise, it proxies closely the estimated economic value (Gambardella et al., 2008). We calculate the total of all forward citations received by an individual patent. We also used a fixed citation window of 3 years with similar findings. In addition, we use a dummy indicating whether the patent is in the top 10% of citations received within 3 years of all patents in our sample.

In line with our hypotheses developed in section 3, we expect a positive correlation between boundary spanning links and forward citations, i.e. Boundary Spanning or Affiliate patents have a higher rate of forward citations as compared to Citing-NonAffiliate patents. When boundary spanning inventor links would be a stronger mechanism to effectively transfer cross-institutional knowledge as compared to an affiliate link, we expect the difference between BoundarySpanning-NonAffiliate patents and Citing-NonAffiliate patents to be larger than between Citing-Affiliate and Citing-NonAffiliate patents (equivalent to BSA > CA). Similarly, BoundarySpanning-Affiliate patents having more forward citations compared to Citing-Affiliate patents would suggest that beyond an affiliate link, a boundary spanning inventor link is able to generate extra value. If inventor and affiliate links are complementary, i.e. boundary spanning inventor links are more effective for affiliated partners and/or affiliated partners get more value out of boundary spanning inventor links, we have BSA patents outperforming both CA and BSNA patents relative to CNA patents, i.e. BSA – CA > BSNA – CNA.

5.2.1.2. Cumulativeness of Innovation

Firms working in a particular technology area can build on their internal knowledge. Self-citations reflect this capacity of the firm to build further on its existing internal technologies. We calculate the proportion of forward citations of our sample patents that are self-citations as an indicator for the fact that firms tend to build on these technologies relative to others building forward on their technologies. Hence, the proportion of self-citations reflects the extent to which the company is able to or attempts to appropriate the returns to its R&D investments (Ahuja, 2003).

In line with our hypotheses developed in section 3, we expect firms with links to IMEC to have a higher capacity to build on their internal knowledge. Particularly the link through boundary spanning inventors should improve this capacity.

5.2.1.3. Technological Lead Time

Citation lags between patents are used to analyze the speed at which the knowledge captured by the invention is assimilated and used to develop subsequent inventions. Here we refer to how fast companies start developing new technologies in the same technology space as the newly developed technologies at IMEC, i.e. we calculate – in years – the citation lag of citations of patents *to* R0 and R1, the base IMEC technologies.

In line with our hypotheses developed in section 3, we expect firms with links to IMEC to be faster in developing new technologies. Particularly the link through inventor mobility should improve this capacity.

5.2.2. Control Variables

To obtain consistent estimates, we include control variables at the invention level, inventor level and firm level.

At the <u>invention level</u>, we first control for 30 *patent technology classes* as defined by Fraunhofer (FhG-ISI, Germany) based on concordance with IPC codes (OECD, 1994). As pointed out by Fabrizio (2009), patents in fast evolving technological classes will cite more recent patents on average so that we need to control for this bias. Also, as illustrated by Hall and Ziedonis (2001), citation lags in computers, communications and electronics are relatively short compared to other technological fields. Moreover, different technological classes are characterized by different citation patterns, both in the amount and the scope of citations to patents and scientific literature. Traditional technological fields typically cite more and are cited less, whereas emerging technological fields are cited more but are average in terms of citations made.

Second, we control for changes in citation patterns over time by including *application year* dummies. At the same time, we include the logarithm of age as an offset to control for the fact that older patents have more time to be cited so that our count measures based on forward citations do not suffer from truncation. [7]

In addition, we introduce *patent scope* as the number of core International Patent Classification (IPC) codes. Patent scope could determine the extent of patent protection and monopoly power and thus the economic value of an invention (Scotchmer, 1991). But, more IPC classes covered by the patent could also affect the likelihood of being cited as the patent covers more technology space. The count of citations to scientific work (NPRS) is included as an additional control as more references to scientific work are associated with a higher number of received citations merely because the act of publication allows the ideas underlying the patent to diffuse more broadly and rapidly (Fleming and Sorenson, 2004). Similarly, we control for the number of backward patent references to control for unobserved factors affecting citation behavior.

[7] To mitigate the truncation bias, Czarnitzki et al. (2008) propose to estimate the model with exposure as explained in Cameron and Trivedi (1998, pp. 303). Hereby, the exposure during which citations might occur is defined as the *age of the patent in 2007.* Alternatively, one can restrict the citation window to 3 or 4 years. Results are not really affected, but it affects the interpretation of the application year dummy.

Finally, we include the *number of inventors* as an additional control because more inventors might lead to a faster and greater diffusion of the tacit and complex knowledge underlying the patent, resulting in different forward citation patterns.

Besides controls at the level of the invention, we include for each patent inventor his *experience* to control for a potential inventor selection issue. Particular types of technologies might be developed by more competent or experienced researchers. We calculate inventor experience as the number of patents filed at the USPTO by the inventors before the application year. We made use of "the careers and co-authorship networks of U.S. patent-holders" data (Lai, D'Amour and Fleming, 2009) to identify inventor histories.

Finally, we introduce for each patent additional measures on the organization of R&D at the firm level to control for firm specific variation. Several stories have been advanced as to why organization size matters for research productivity. First, larger organizations wield more resources and are able to exploit economies of scale in research (Cassiman et al., 2005). Cassiman, Perez-Castrillo and Veugelers (2002) find that larger firms have an incentive to proportionally invest more in basic research as it increases the productivity of applied R&D. Second, larger organizations allow more specialization. In larger firms, researchers seem to work on more projects but are more specialized in the type of projects they engage in (Kim et al., 2004). Third, larger companies are able to exploit economies of scope. As larger firms are active in different product markets and technology domains, more opportunities for exploiting economies of scope within the firm arise (Cassiman et al., 2005; Henderson and Cockburn, 1996). *Scale* is calculated as the number of US patents filed by the firm in the 5 years before the application year of the patent, *Scope* as the number of distinct IPC codes of a company's patents in the 5 years before the application year of the patent and *Age Company* as the number of years since the company's first patent at the moment of the filing of the focal patent.[8] Sorenson and Stuart (2000) find that on the one hand older firms produce more patents, but on the other hand these same firms produce less valuable patents. Older firms self-cite more and have older backward citations.[9] In addition, we also include *firm fixed effects* to capture unobserved heterogeneity across companies.

5.3. Descriptive analysis

Table 1 presents an overview of all the patents in our sample categorized according to our methodology and by technology field. IMEC patents are predominantly classified as semiconductor patents. As for partner and non-partner patents we observe more variety in technology field as we are moving closer to applications.

Insert TABLE 1 here

Table 2 shows all the firms listed in the top25 of firms in the semiconductor industry based on sales between 1987 and 2008 (Source: iSuppli corporation ranking). Of the 43 firms appearing in the list between 1987 and 2008, 20 firms are IMEC affiliated partners during the entire period. We can also appreciate IMEC's position in the global semiconductor industry from the fact that although not all firms are IMEC IIAP partners, all but 14 firms (of which 6 more recently affiliated partners) are represented in our dataset through patents linking to IMEC.

Insert TABLE 2 here

Table 3 presents some descriptive statistics for the total sample, while Table 4 gives an overview of descriptive statistics by type of patent. The IMEC patents (R0-R1)

[8] These firm-level variables vary across different patents of the same company applied for at different moments in time.

[9] Note that their interpretation of self-citations does not necessarily correspond to our notion of appropriation in science intensive businesses. See also Catani (2005) for a similar interpretation of self-citations in optical fiber technology.

have fewer backward citations (patent references) and are more likely to cite the scientific literature (non-patent reference binary), confirming the more “basic” and original nature of these patents. 14% of the R0 patents are co-developed with universities illustrating IMEC’s strategy to collaborate with academics in order to build up its background knowledge and confirming its role as bridging institution.

When we look at the company patents, we see that BoundarySpanning-Affiliate patents, which have both a boundary spanning inventor and affiliate link to IMEC, receive the highest number of forward citations. This is particularly clear when we restrict the citation window to 3 years, controlling for the exposure time of patents. These patents also have a higher probability to be a “highly cited” patent. Citing-Affiliate patents with only an affiliate link to IMEC, but without the boundary spanning inventor link, are as likely as BoundarySpanning-Affiliate patents to receive forward citations, but the count of these citations are lower, and the probability of being a “highly cited” patent is also lower. Both BoundarySpanning-Affilitate and Citing-Affiliate patents are more likely to be built upon internally as the partner is more likely to continue developing technology in that area. Self-citations of these patents are much higher and these patents themselves come sooner after initial IMEC background technology has been developed. Given the strategic importance of technology lead time in the industry, we find that patents with boundary spanning inventors and/or organizational links with IMEC have an average citation lag roughly between 2 and 3 years while patents without any link have an average citation lag of 9.7 years.

In summary, these first descriptive results already indicate that the tighter the link with IMEC, the faster a company seems able to assimilate the knowledge captured by the invention and to use this knowledge to develop subsequent inventions.

We argued that because of the tacitness and complexity of know how underlying leading edge research, researcher interaction and mobility does play an essential role. We indeed observe that individual inventors from affiliated partners visiting the research center in order to collaborate with other industrial and scientific researchers in joint R&D projects – i.e. boundary spanning inventors – seem to play a decisive role as link between industry and science. These descriptive statistics are already supportive for the positive impact of IMEC links for technology development, particularly the combined inventor and organizational link. But as we do not control for differences across application years, technology classes and firms, these findings still await confirmation from multivariate analysis.

Insert TABLE 3 & 4 here

5.4. Multivariate Methodology

5.4.1. Quality of Innovation

To estimate the technological impact of the patents as measured by their number of forward citations, we use count models as the dependent variable is a non-negative integer. The specification of our baseline model as a Poisson or a Negative binomial model follows previous studies. We first estimate the Poisson quasi-maximum likelihood model (PQML) because this renders consistent estimates given that the mean is correctly specified (Gouriéroux et al., 1984). However, Hausman et al. (1984) propose to use a Negative Binomial model which allows for overdispersion and heterogeneity across observations. Moreover, our sample has a large number of observations with zero value (31% of 1,089 patents). To deal with this issue, a Zero-Inflated Negative Binomial model (ZINB) is estimated whereby the population is divided between two latent groups, the always-zero group, i.e. patents that will never receive a citation, and the not-always-zero group, i.e. patents which at least have the potential of receiving citations (Long, 1997). A logit model is used to determine to which part of the population an observation belongs while the estimated counts are obtained via a Negative Binomial specification. Finally, we estimate a probit model with being a highly cited patent as dependent variable.

5.4.2. Cumulativeness of Innovation

To estimate the importance of building further internally on IMEC related technology we regress the proportion of self-citations of the patent on our control variables and patent indicators for the type of link with IMEC. We use OLS and heteroskedastic Tobit models to control for censoring of the observations.

5.4.3. Technological Lead Time

To estimate the speed at which research teams with different inventor- and organizational-level links with science through the research center assimilate science-related prior art and develop subsequent inventions building on this prior art, we use forward citation lags, i.e. the lag in years between the publication date of the cited patent application – R0 or R1 in this case – and the application date of the citing patent application, as dependent variable. We apply a simple OLS specification with robust standard errors clustered by citing firm.

6. Results

6.1. Quality of Innovation

Table 5 shows the results of our count model estimations. Patents of affiliated partner companies (with or without boundary spanning inventor) receive between 2.9 and 28 times more citations compared to the control group of patents assigned to non-affiliated companies. As we find evidence that patents developed by affiliated-partners without the support of boundary spanning inventors have a larger technological impact compared to patents developed by non-affiliated organizations, this suggests that *internal spillover* effects exist among company researchers involved in more experimental, science-related research and company researchers involved in the development of commercial end-user applications.[10]

Our expectation that patents developed by affiliated companies with the assistance of boundary spanning inventors, are more valuable and have a larger technological impact compared to patents developed by affiliated companies without the assistance from boundary spanning inventors seems to hold in the Negative Binomial and the Zero-Inflated Negative Binomial models, but the difference in coefficients is not statistically significant.

The boundary spanning inventor link for non-affiliate partners does show up with more forward citations compared to the control group suggesting that non-affiliated companies might benefit from cross-institutional employee interaction and mobility by hiring away researchers from partner companies. But this effect only shows up in the Poisson models and is only marginally significant.

The combination of the low (and often insignificant) coefficient for BoundarySpanning-NonAffiliate patents and the minimal difference between the coefficients of BoundarySpanning-Affiliate and Citing-Affiliate patents are not supportive of our hypotheses that when comparing the organizational and the boundary spanning inventor link, the latter one is the strongest and can generate the

[10] To further analyze the importance of internal links between boundary spanning inventors and company researchers not visiting IMEC, we looked for patents without boundary spanning inventors which have an inventor which is also mentioned as inventor on a patent together with boundary spanning inventors of the same company but not as inventor on a R0/R1 patent. This is the case in only 10 of the 435 R3 patents.

most extra value. Nor is there any strong evidence of complementarity between the two links. The results rather seem to indicate it is the affiliate link that matters more than the boundary spanning inventor link. At the same time this result might raise some concern about partner selection issues and unobserved heterogeneity in general. We deal with this issue in Section 6.4 where we discuss the robustness of our findings. In line with predictions from previous research, the count of IPC classes and the count of citations to scientific literature are positively related to the number of forward citations and the age of a company is negatively related to the number of forward citations.

Insert TABLE 5 here

Table 6 presents the results on the probability to be a highly cited patent (i.e. receiving more than 8 citations in the 3year window, which is the case for 10% of the patents in our sample) as dependent variable. The results confirm the previous analysis, with affiliate companies being more likely to develop breakthrough inventions. Both BoundarySpanning-Affiliate and Citing-Affiliate patents are significantly positive, but in this case, the marginal effect for BoundarySpanning-Affilitate patents the larger of the two, in favor of a complementary effect between both links. This suggests that for delivering breakthrough innovations, the boundary spanning inventor link is important for affiliate companies and not for other companies. Patents from affiliated firms with a boundary spanning inventor link have a 51% higher probability a being a highly cited patent. This compares to a 35% higher probability for patents from affiliated firms without a boundary spanning inventor link. Maybe somewhat surprisingly, BoundarySpanning-NonAffiliate patents are not more likely to be highly cited.

Insert Table 6 here

6.2. Cumulativeness of Innovation

Building further on technology linked to IMEC technologies is an important way to capitalize and appropriate returns to the R&D investment. As expected, IMEC partners are more likely to build further on these technologies, as indicated by the higher proportion of self-citations received by BoundarySpanning-Affiliate and Citing-Affiliate patents. This result is in line with Ziedonis and Ziedonis (2005), which find that member firms of the SEMATECH consortium are building upon the results of their collective research to a greater degree than are non-member firms. These patents are expected to have on average a 29% to 34% larger proportion of self citations relative to comparable patents by non-affiliates. As a result, we clearly do find an IMEC-effect as affiliate partners are more active in building on these technologies, even in the absence of a boundary spanning inventor link. Nevertheless, we find that partner patents with a boundary spanning inventor link have an even larger proportion of self citations compared to patents of affiliate partners without a boundary spanning inventor link. This finding suggest the complementary role of boundary spanning inventors for affiliated partners in order to better absorb the complex and tacit technological knowledge underlying micro-electronics research via mobility and communication, appropriating returns to the R&D investment through the internal development of the next generation of technologies. However, the coefficients are not significantly different.

A non-affiliate patent with a boundary spanning inventor link has a smaller proportion of self citations. This result seems to suggest that the hiring company is not able to fully appropriate the return to its investments relative to others building forward on the technologies developed by this researcher. Being able to fully exploit the researcher mobility link seems to require a complementary institutional link.

Insert TABLE 7 here

6.3. Technological Lead Time

We argued that time-to-market and lead time of innovation projects are increasingly a differentiator in the micro-electronics business because of the relentless shortening of product life cycles. The results displayed in Table 8 show that patents from affiliated firms and (co-)developed by boundary spanning researchers are fastest in citing the more basic, science-related IMEC patents (R0, R1). The technology lead time between the publication of the prior art and the filing of a new patent building forward on this prior art is expected to be 3 years and 3 months shorter compared to patents without any links, a result which is both statistically and economically significant. The fact that the difference in expected citation lag between partner patents with and without boundary spanning inventor links is statistically significant suggests that the bridging researchers play a key role in assimilating the science-related prior art and in reducing lead time of the next generation of technologies built on this prior art. Also supportive of the importance of the boundary spanning inventor link, is the result that the coefficient for BoundarySpanning-NonAffiliate patents is significantly negative. Hiring away an affiliated or visiting researcher enables also non-partner firms to keep up with technological progress and reduce lead time with respect to non-partner companies. Nevertheless, the significantly lower coefficient for BoundarySpanning-Affiliate patents compared to both Citing-Affiliate and BoundarySpanning-NonAffiliate patents indicates that the boundary spanning inventor link is particularly important to generate technology lead time in combination with an affiliate link. Poaching of IMEC related inventors is less effective for non-affiliated partners to establish technology lead time.

Unfortunately, these results are not robust to the inclusion of firm dummies, suggesting that there are important company characteristics beyond IIAP affiliation and other firm controls included, that need to be factored in to explain the acquisition of technology lead time.

Finally, we find that the citation lag between two technologically similar patents or between patents developed by the same inventor(s) is shorter, although the latter effect is not significant.

Insert TABLE 8 here

6.4. Robustness Checks

While the empirical results are supportive for the tangible effects of links with IMEC, we need to address potential selection issues at the level of the technology, inventor or partner firm. First, one could argue that the IMEC related technology is a better technology and would get cited more anyway. However, without IMEC these BoundarySpanning-Affiliate technologies would not exist, so it is difficult to come up with an alternative counterfactual other than the one we have, i.e. comparing BoundarySpanning-Affiliate technologies to the relevant Citing-NonAffiliate technologies. On average the IMEC related technologies are of higher quality as shown in the results of Table 5, controlling for other characteristics of the technology, patents, inventors and the firms.

Second, there might also be an inventor selection issue in case firms would typically send their more competent researchers to IMEC. From interviews with managers from IMEC we learned that this is not necessarily the case because companies do not want to share their most valuable human resources with other firms -including competitors- while at the same time making sure that the participating researchers are able of identifying, absorbing and integrating the relevant knowledge.

IMEC does attempt to control such behavior by providing affiliates with regular evaluations of the affiliate researchers in the IMEC teams. We attempted to test the inventor selection issue by matching the prior patents of IMEC-visiting researchers, i.e. prior to these visits, with a group of comparable patents applied for by the same firm within the same year. Results obtained from T-tests indicate that the paired group of patents do not differ significantly,[11] suggesting that there is no obvious inventor selection issue.[12]

Beyond the inventor selection issue, one could argue that firms which expect to get more out of such a partnership are more likely to become a partner in the first place. At the same time there might also exist alternatives to IMEC as a research partner. However, 15 of the largest semiconductor companies between 1987 and 2008 not engaged in IIAP are also represented in our dataset through citations to IMEC patents or by hiring away researchers from partner firms, indicating that these technologies seem also important for non-partner companies. For example, IBM has organized a parallel network for developing technologies in the same technology area as IMEC. Nevertheless, this network is organized very differently compared to the IMEC affiliate program. As our results show (and for results not shown where we restrict the control sample to patents of these firms), IMEC affiliates seem to generate better results in the technological areas where IMEC operates compared to non-partner companies.

To formally control for a partner selection issue, we estimated the probability of a particular patent to be an affiliate partner patent at a particular moment in time in function of patent characteristics, a company's core technological area (8 categories),

[11] We found no statistically significant differences between the number of citations received within three years, the proportion of self citations, the number of IPC codes, the number of backward patent citations, the number of non-patent references and the number of inventors.

[12] In the case that partners are likely to send less competent researchers, this would actually bias the results agains us.

the location of its headquarters (USA/Europe/Japan), whether the firm is in the top 25 of largest semiconductor firms as well as its scale, scope and age. The selection model makes 82% correct predictions. Consequently, we calculate the propensity scores to be a partner patent and link each partner patent to the nearest neighbor non-partner patent, i.e. we compare BoundarySpanning-Affiliate and Citing-Affiliate patents with BoundarySpanning-NonAffiliate and Citing-NonAffiliate patents not on average, but as closest neighbor. Results are presented in Table 9. The matched patents reveal a similar story as from our regressions with some interesting nuances. Boundary spanning inventors of affiliate partners matter for the quality of the technologies developed as shown for the forward citations and the highly cited patents. These results are not as strong for the Citing-Affiliate versus Citing-NonAffiliate patents. On the contrary, self-citing seems more relevant for affiliate firms and is less directly related to the boundary spanning inventors. But overall our findings in the previous sections do not seem driven by a partner selection effect.

Insert TABLE 9 here

7. Discussion and Conclusion

In conclusion, we find strong support for IMEC affiliated partners to develop higher quality innovations in the technology domain where IMEC is active. Furthermore, partner firms are more likely to build on these technologies internally, improving appropriation of the returns to R&D. Finally, the IMEC partner firms are faster on the ball, linking faster to these new technologies. Overall, we therefore conclude that institutionally linking to IMEC has provided some tangible benefits for IMEC partners.

We have found that the boundary spanning inventors, i.e. researchers of a partner actively engaged in joint research with IMEC are an important link in this chain as they allow the partner to develop higher quality innovations but in particular as they allow to capitalize the returns to R&D through a faster internal development of the next generation of commercial technologies. The technologies developed by the bridging researchers are extensively used internally as a platform for further technology development.

As these effects from boundary spanning inventor links are most strongly found for IMEC partners, this suggests that companies should have a complementary institutional link to benefit from cross-institutional employee interaction and mobility, in particular for the appropriation of returns to R&D through establishing cumulative technology development and lead time.

Although the results are very supportive of tangible benefits for IMEC partners, they nevertheless also suggest important avenues for further research. Particularly the significance of the firm dummies suggests that there are critical company characteristics beyond the scale and scope of R&D, the age of a company and IIAP affiliation that need to be factored in to explain appropriation success. More information on how firms organize internal spillovers across projects would be important and interesting complementary information.

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Figure 1: Final Sample Construction

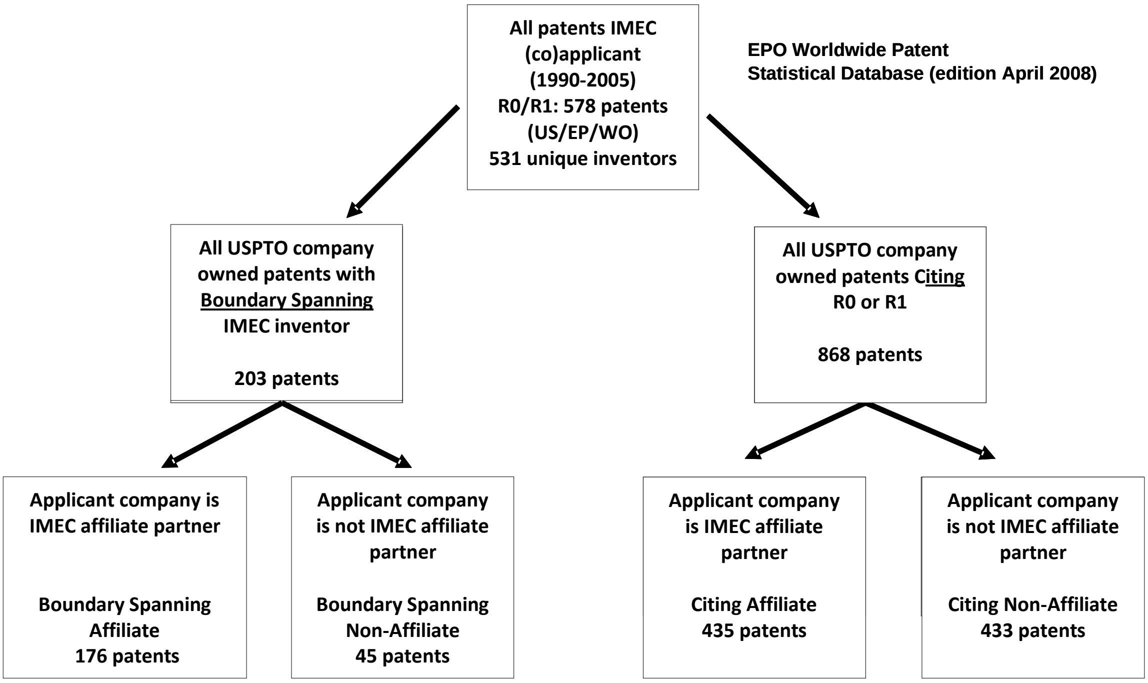

Figure 2: Classification of Patents

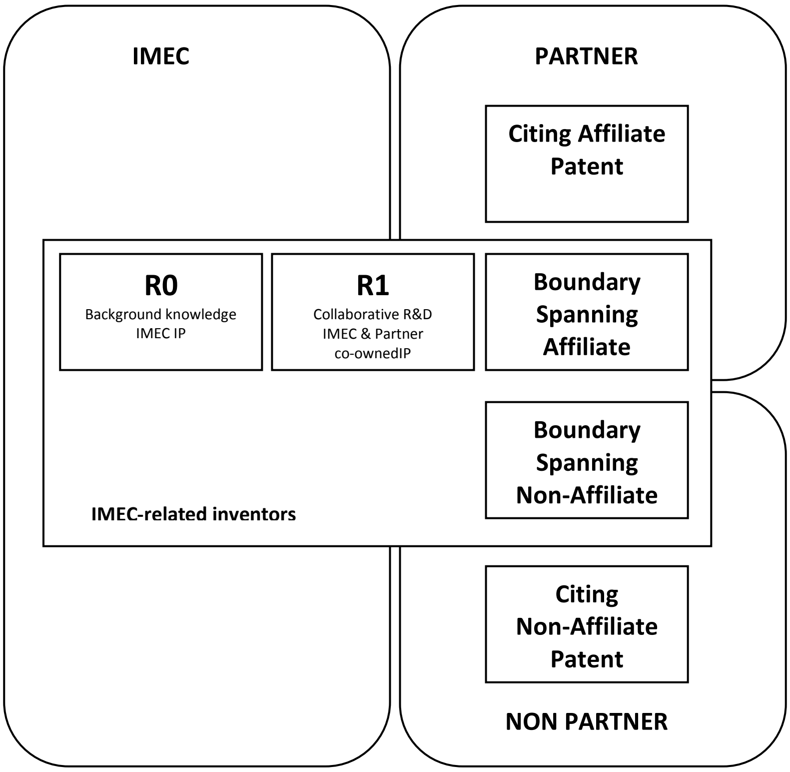

TABLE 1: Patents by Technology Field

	IMEC		IMEC AFFILIATE		NON-IMEC AFFILIATE	
FIELD	R0	R1	BOUNDARY SPANNING INVENTOR	NO BOUNDARY SPANNING INVENTOR	BOUNDARY SPANNING INVENTOR	NO BOUNDARY SPANNING INVENTOR
Electrical machinery and apparatus, electrical energy	4%	2%	4%	5%	5%	5%
Telecommunications	11%	8%	10%	8%	12%	9%
Information technology	6%	7%	4%	6%	6%	5%
Semiconductors	36%	41%	34%	27%	32%	26%
Optics	10%	8%	11%	13%	9%	13%
Analysis, measurement, control technology	10%	10%	7%	8%	6%	8%
Macromolecular chemistry, polymers	2%	5%	5%	3%	3%	3%
Chemical engineering	2%	2%	1%	2%	2%	2%
Surface technology, coating	3%	4%	3%	5%	4%	4%

TABLE 2: Ranking Semiconductor Companies

RANKING BASED ON REVENUES 2008	COMPANY	MARKET SHARE 2008	IMEC PARTNER	R1	Boundary Spanning Affiliate Patent	Citing Affiliate Patent	Boundary Spanning Non-Affiliate Patent	Citing Non-Affiliate Patent
				ALL	US ONLY	US ONLY	US ONLY	US ONLY
1	INTEL	13.10%	YES	1		67		
2	SAMSUNG	7.00%	YES	10		30		
3	TOSHIBA SEMICONDUCTORS	4.30%						19
4	TEXAS INSTRUMENTS	4.30%	YES	11	43	15		
5	STMICROELECTRONICS	4.00%	YES	8	3	6		
6	RENESAS TECHNOLOGY	2.70%	YES	1		4		
7	SONY	2.70%	YES	3		5		
8	QUALCOMM	2.50%	YES					
9	HYNIX	2.30%	YES					
10	INFINEON	2.30%	YES	7	4	20		
11	NEC	2.30%						27
12	ADVANCED MICRO DEVICES	2.10%	YES		26			
13	FREESCALE SEMICONDUCTORS	1.90%						4
14	BROADCOM	1.80%						21
15	PANASONIC	1.70%	YES					
16	MICRON	1.70%	YES			101		
17	NXP	1.60%	YES					
18	SHARP	1.40%						11
19	ELPIDA MEMORY	1.40%	YES					
20	ROHM	1.30%	YES					
21	NVIDIA	1.30%						
22	MARVELL TECHNOLOGY GROUP	1.20%						
23	MEDIATEK	1.10%						
24	FUJITSU MICROELECTRONICS	1.10%	YES		1	17		
25	ANALOG DEVICES	1.00%						
	OTHER PLAYERS IN TOP 20 FROM 1987 TO 2007							
	AGERE							
	AT&T							5
	GENERAL ELECTRIC							10
	HITACHI SEMICONDUCTORS		YES			19		
	HYUNDAI SEMICONDUCTORS							6
	IBM MICROELECTRONICS						4	43
	LG							6
	LUCENT TECHNOLOGIES						3	18
	MATSUSHITA ELECTRIC							13
	MITSUBISHI SEMICONDUCTORS						5	11
	MOTOROLA SEMICONDUCTORS							13
	NATIONAL SEMICONDUCTOR		YES	1		4		
	OKI SEMICONDUCTORS							5
	PHILIPS SEMICONDUCTORS		YES	43	7	8		
	SANYO SEMICONDUCTORS							
	SGS THOMSON							
	SIEMENS SEMICONDUCTORS		YES	13	8	2		
	SPANSION							
	SUM				92	298	12	212
	% OF SAMPLE				52%	69%	27%	49%

TABLE 3: Descriptive Statistics

	Description	Obs	Mean	Std Dv	Min	Max
Count forward citations	The number of times a patent is cited as prior art by subsequent patents	1089	5.31	11.01	0	131
Count forward citations within 3 years	The number of times a patent is cited as prior art by subsequent patents within three years after publication	1089	2.87	5.17	0	61
Forward citations binary	Dummy indicating whether a patent received citation(s)	1089	0.69	0.46	0	1
Dummy highly cited	Dummy indicating whether the patent received 8 citations or more within 3 years	1089	0.10	0.31	0	1
Count forward self citations	The number of times a patent is cited by patents assigned to the same company	1089	1.31	5.49	0	116
Count forward self citations within 3 years	The number of times a patent is cited by patents of the same company within three years after publication	1089	0.81	2.23	0	27
Proportion forward self citations	The number of self citations divided by total amount of forward citations	1089	0.17	0.31	0	1
Forward self citations binary	Dummy indicating whether a patent received self citation(s)	1089	0.32	0.47	0	1
Patent scope / Count IPCs	The number of IPC codes	1089	2.58	2.07	1	14
Count non-patent references (NPRS)	The number of non-patent citations	1089	7.76	15.53	0	99
Count patent references (PRS)	The number of patents cited by the patent	1089	30.41	31.43	0	147
Count inventors	The number of inventors on the patent	1089	2.94	2.10	1	15
Inventor experience / Count patents ('000)	The number of patents (in '000) applied for by the inventors before the application	1089	0.07	0.15	0	2
Scale / Count patents last 5 years ('000)	The number of patents (in '000) the applicant company applied for in the last 5 years before the application	1089	4.25	4.39	0	20
Scope / Count IPC's last 5 years ('000)	The number of unique IPC codes (in '000) appearing on the company's patents applied for in the last 5 years before the application	1089	1.27	1.16	0	5
Age company	The number of years since the company's first patent	1089	50.92	28.19	4	109
Citation lag R0 cited	The number of years between the publication date of the cited patent and the application date of the citing patent	2103	7.16	14.28	0	81
Citation lag R1 cited		564	7.47	15.98	0	80
Citation lag R0/R1 cited		2667	7.22	14.66	0	81
Dummy same IPC	Dummy indicating whether the cited and the citing patent share at least one IPC code	2667	0.41	0.49	0	1
Dummy same inventor	Dummy indicating whether the cited and the citing patent share at least one inventor	2667	0.02	0.15	0	1
Dummy same applicant	Dummy indicating whether the cited and the citing patent share at least one same applicant	2667	0.01	0.10	0	1

TABLE 4: Descriptive Statistics by Patent Type

	IMEC		IMEC AFFILIATE		NOT IMEC-AFFILIATE	
	R0	R1	BOUNDARY SPANNING INVENTOR	NON-BOUNDARY SPANNING INVENTOR	BOUNDARY SPANNING INVENTOR	NON-BOUNDARY SPANNING INVENTOR
Count forward citations	7.32	7.67	7.16	4.40	5.13	5.48
Count forward citations within 3 y	3.05	4.15	4.41	2.38	1.64	2.86
Forward citations binary	0.78	0.67	0.65	0.66	0.56	0.76
Dummy highly cited patent	0.07	0.11	0.15	0.09	0.07	0.10
Count forward self citations	0.67	1.33	2.46	1.40	0.24	0.87
Count forward self citations within 3 y	0.27	0.70	1.28	0.90	0.11	0.61
Proportion forward self citations	0.12	0.15	0.21	0.20	0.05	0.13
Forward self citations binary	0.29	0.30	0.36	0.35	0.13	0.31
Citation lag R0 cited			2.09	3.07	2.89	9.23
Citation lag R1 cited			2.08	2.36	1.50	11.95
Citation lag R0/R1 cited			2.09	2.88	2.54	9.71
Patent scope / Count IPCs	2.44	3.22	2.84	2.36	2.62	2.69
Count non-patent references (NPRS)	6.69	6.83	7.03	7.17	2.78	9.16
Non-patent references binary	0.83	0.72	0.61	0.60	0.51	0.65
Count patent references (PRS)	10.07	13.24	17.51	36.39	19.64	30.76
Count inventors	3.33	4.11	3.43	2.81	2.58	2.90
Inventor experience / Count patents (‘000)			0.04	0.10	0.04	0.04
Scale / Count patents last 5 years (‘000)			2.06	5.84	3.51	3.62
Scope / Count IPC’s last 5 years (‘000)			0.82	1.61	1.28	1.12
Age company			44.23	56.00	46.44	49.02

TABLE 5: Count Forward Patent Citations

	Poisson Quasi Maximum Likelihood			Negative binomial	Zero-inflated Negative binomial		Count forward citations within 3 years
	(1)	(2)	(3)	(4)	(5) Count	(6) Logit	(7)
BOUNDARY SPANNING	0.8686*	0.7501	1.3843**	2.4541***	3.3658***	0.3445	2.8030***
AFFILIATE	[0.5146]	[0.5553]	[0.5897]	[0.7031]	[0.6696]	[0.2577]	[0.6219]
CITING-AFFILIATE	1.0370***	0.9893***	1.6317***	2.2643***	3.0687***	0.4167**	2.8601***
	[0.2868]	[0.3177]	[0.3736]	[0.3651]	[0.2867]	[0.1824]	[0.3495]
BOUNDARY SPANNING	0.8147*	0.7394*	0.7532*	0.1199	0.4593	0.7419	-0.0832
NON-AFFILIATE	[0.4194]	[0.4326]	[0.4388]	[0.5471]	[0.4769]	[0.5373]	[0.3086]
PATENT CHARACERISTICS							
Count IPCs		0.0700***	0.0702***	0.1029***	0.0565**	-0.3087***	0.0926***
		[0.0197]	[0.0194]	[0.0225]	[0.0236]	[0.0692]	[0.0181]
NPRS		0.0117***	0.0116***	0.0097***	0.0049*	-0.0295	0.0099***
		[0.0021]	[0.0022]	[0.0036]	[0.0030]	[0.0209]	[0.0032]
PRS		-0.0092***	-0.0091***	-0.0023	-0.0024	0.0035	-0.0052*
		[0.0019]	[0.0019]	[0.0027]	[0.0021]	[0.0043]	[0.0030]
Count inventors		0.0005	0.0002	-0.0362	-0.0183	0.0610	-0.0133
		[0.0316]	[0.0300]	[0.0295]	[0.0248]	[0.0411]	[0.0217]
Log(age)		1	1	1	1		
INVENTOR CHARACTERISTICS							
Inventor experience			-0.0034	0.4254	-0.1615	-2.4360	0.5046
			[0.5086]	[0.3455]	[0.1956]	[1.6481]	[0.4298]
FIRM CHARACTERISTICS							
Scale			-0.0166	0.0026	-0.0187	-0.0010	0.0700
			[0.0585]	[0.0519]	[0.0461]	[0.0260]	[0.0965]
Scope			-0.0763	0.5246	0.5841	-0.0979	0.5360
			[0.4993]	[0.4381]	[0.4130]	[0.1153]	[0.4728]
Age company			-0.1332***	-0.1490***	-0.1710***	0.0068**	-0.1599***
			[0.0160]	[0.0200]	[0.0168]	[0.0035]	[0.0161]
Constant	0.2913	0.6032	2.1598***	2.1104***	2.2040***	-13.8528***	-15.8982
	[0.4368]	[0.4404]	[0.4569]	[0.4727]	[0.3765]	[1.1999]	[0.0000]
Test of joint significance							
Firm dummies	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***		Incl.***
Technology class	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***
Application year	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***	Incl.
Overdispersion parameter (ln alpha)				0.5407***	-0.5284***		
				[0.0804]	[0.0956]		
Vuong test					12.75***		
Log LH/PLH	-18724.434	-17949.444	-17936.513	-4012.5821	-3801.036		-2491.848
Observations	1089	1089	1089	1089	1089	1089	1089

All regressions include application year, technology and firm dummies, R5 is control group

Robust standard errors in brackets, clustered by firm,

*** p<0.01, ** p<0.05, * p<0.1

Marginal Effects (3): BoundarySpanning-Affiliate 299%**; Citing-Affiliate 411%***; BoundarySpanning-NonAffiliate 112%*

TABLE 6: Marginal Effects Dummy Highly Cited Patent

	Probit		
	(1)	(2)	(3)
BOUNDARY SPANNING	0.5361***	0.5157***	0.5154***
AFFILIATE	[0.0576]	[0.0665]	[0.0330]
CITING-AFFILIATE	0.3512***	0.3434***	0.3508***
	[0.0554]	[0.0547]	[0.0570]
BOUNDARY SPANNING	0.0784	0.0672	0.0598
NON-AFFILIATE	[0.0845]	[0.0787]	[0.0719]
PATENT CHARACERISTICS			
Count IPCs		0.0083*	0.0078*
		[0.0046]	[0.0045]
NPRS		0.0010**	0.0010**
		[0.0005]	[0.0005]
PRS		-0.0005	-0.0004
		[0.0005]	[0.0005]
Count inventors		0.0077	0.0090*
		[0.0052]	[0.0048]
INVENTOR CHARACTERISTICS			
Inventor experience			-0.0123
			[0.0560]
FIRM CHARACTERISTICS			
Scale			0.0151
			[0.0113]
Scope			-0.0550
			[0.0723]
Age company			-0.0066
			[0.0042]
Test of joint significance			
Firm dummies	Incl.***	Incl.***	Incl.***
Technology class	Incl.***	Incl.**	Incl.***
Application year	Incl.***	Incl.***	Incl.***
Observations	1089	1089	1089
Pseudo R-squared	0.359	0.372	0.380
% Correctly predicted	91.2%	91.4%	91.4%

Marginal effects reported, All regressions include application year, technology and firm dummies, R5 is control group
Robust standard errors in brackets, clustered by firm,
*** p<0.01, ** p<0.05, * p<0.1

TABLE 7: Proportion Self Citations

	OLS			HETORSKEDASTIC TOBIT		
	(1)	(2)	(3)	(4)	(5)	(6)
BOUNDARY SPANNING AFFILIATE	0.1775**	0.2188**	0.1833**	2.6757***	2.7778***	2.6890***
	[0.0732]	[0.0909]	[0.0850]	[0.5349]	[0.6049]	[0.6612]
CITING AFFILIATE	0.1165**	0.1403*	0.1118*	2.5090***	2.5745***	2.5197***
	[0.0559]	[0.0746]	[0.0642]	[0.4512]	[0.5126]	[0.5638]
BOUNDARY SPANNING NON-AFFILIATE	0.0055	0.0128	-0.0020	-0.2646	-0.2423	-0.3228
	[0.0855]	[0.0941]	[0.0950]	[0.3213]	[0.3476]	[0.3588]
PATENT CHARACERISTICS						
Count IPCs		0.0001	0.0009		0.0028	0.0054
		[0.0049]	[0.0046]		[0.0115]	[0.0111]
NPRS		0.0013	0.0011		0.0037	0.0030
		[0.0013]	[0.0012]		[0.0027]	[0.0023]
PRS		0.0011	0.0012		0.0019	0.0022
		[0.0010]	[0.0008]		[0.0024]	[0.0021]
Count inventors		-0.0033	-0.0002		0.0032	0.0076
		[0.0053]	[0.0060]		[0.0205]	[0.0220]
Count for citations	0.0015*	0.0015*	0.0014*	0.0081**	0.0080**	0.0080**
	[0.0008]	[0.0008]	[0.0008]	[0.0034]	[0.0037]	[0.0035]
INVENTOR CHARACTERISTICS						
Inventor experience			-0.1244			-0.3090
			[0.0867]			[0.5158]
FIRM CHARACTERISTICS						
Scale			-0.0323*			-0.1441***
			[0.0170]			[0.0531]
Scope			0.0340			0.5914*
			[0.0925]			[0.3406]
Age company			0.0027***			0.0208
			[0.0005]			[0.0143]
Constant		-0.1195	-0.1574**	-3.0716	-3.2098	-3.3658
		[0.0823]	[0.0642]	[5.1842]	[2.6481]	[5.3229]
Test of joint significance						
Firm dummies	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***
Technology class	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***
Application year	Incl.***	Incl.***	Incl.***	Incl.**	Incl.***	Incl.
Censoring (at 0 or 1)				75%	75%	75%
Heteroskedasticity test				12.87**	10.54**	12.77**
Log PLH				-665.010	-661.229	-655.754
Observations	1089	1089	1089	1089	1089	1089
(Pseudo) R-squared	0.236	0.247	0.258	0.211	0.215	0.222

All regressions include application year, firm and technology dummies, R5 is control group

Robust standard errors in brackets, clustered by firm, heteroskedasticity term includes 4 scale class dummies

*** p<0.01, ** p<0.05, * p<0.1

Marginal Effects (6): BoundarySpanning-Affiliate 34%***, Citing-Affiliate 29%***, BoundarySpanning-Non-Affiliate -3%

TABLE 8: Citation Lag R0/R1 Cited

	Citation lag			
	OLS			
	(1)	(2)	(3)	(4)
BOUNDARY SPANNING	-3.2865*	-3.2526*	-3.2439**	-0.4159
AFFILIATE	[1.7343]	[1.7452]	[1.3327]	[2.0684]
CITING-AFFILIATE	-0.9157**	-0.9289**	-0.9276**	0.0540
	[0.4337]	[0.4225]	[0.4217]	[1.4724]
BOUNDARY SPANNING	-1.2599**	-1.2466**	0.3243	-0.8000
NON-AFFILIATE	[0.5937]	[0.6075]	[1.9060]	[0.8325]
Count inventors		0.0017	-0.0183	0.0329
		[0.0731]	[0.0725]	[0.0496]
Count core IPC		0.0609	0.0844	0.0159
		[0.1306]	[0.1276]	[0.0955]
NPRS		-0.0266	-0.0229	0.0017
		[0.0290]	[0.0292]	[0.0259]
PRS		-0.0273	-0.0332	-0.0284
		[0.0354]	[0.0355]	[0.0319]
Dummy same IPC			-1.4960***	-0.7453***
			[0.2512]	[0.2370]
Dummy same inventor			-1.9609	-0.0921
			[2.1498]	[0.8506]
Dummy same applicant			4.6324**	1.6792
			[2.1003]	[2.0132]
Constant	15.1701***	15.2123***	16.9086***	13.9315
	[2.4890]	[2.5348]	[2.5271]	[11.4845]
Test of joint significance				
Firm dummies				Incl.***
Technology class cited	Incl.***	Incl.***	Incl.***	Incl.***
Technology class citing	Incl.***	Incl.***	Incl.***	Incl.***
Application year cited	Incl.***	Incl.***	Incl.***	Incl.***
Publication authority	Incl.***	Incl.***	Incl.***	Incl.***
Observations	2667	2667	2667	2667
R-squared	0.669	0.670	0.672	0.947

All regressions include application year, patent authority and technology dummies, R5 is control group
Robust standard errors in brackets, clustered by firm
*** p<0.01, ** p<0.05, * p<0.1

TABLE 9: Matched Partner/Non-Partner Patents

				TTEST	
		PARTNER (TREATED)	NON-PARTNER (NON-TREATED)	t	P>|t|
		BOUNDARY SPANNING AFFILIATE vs BOUNDARY SPANNING NON-AFFILIATE			
Count forward cit 3y	**Unmatched**	4.41	1.64	1.97	0.050
	Matched	4.41	1.55	4.02	0.000
Dummy highly cited	**Unmatched**	0.15	0.07	1.44	0.152
	Matched	0.15	0.04	3.53	0.000
Proportion self citations	**Unmatched**	0.21	0.05	2.98	0.003
	Matched	0.21	0.30	-2.90	0.004
		BOUNDARY SPANNING AFFILIATE vs CITING NON-AFFILIATE			
Count forward cit 3y	**Unmatched**	4.41	2.86	2.88	0.004
	Matched	4.41	0.72	5.13	0.000
Dummy highly cited	**Unmatched**	0.15	0.10	1.71	0.088
	Matched	0.15	0.02	4.30	0.000
Proportion self citations	**Unmatched**	0.21	0.13	2.96	0.003
	Matched	0.21	0.04	5.79	0.000
		CITING AFFILIATE vs BOUNDARY SPANNING NON-AFFILIATE			
Count forward cit 3y	**Unmatched**	2.38	1.64	1.28	0.200
	Matched	2.38	2.67	-1.30	0.195
Dummy highly cited	**Unmatched**	0.09	0.07	0.61	0.542
	Matched	0.09	0.14	-1.92	0.056
Proportion self citations	**Unmatched**	0.20	0.05	2.95	0.003
	Matched	0.20	0.09	5.81	0.000
		CITING AFFILIATE vs CITING NON-AFFILIATE			
Count forward cit 3y	**Unmatched**	2.38	2.86	-1.81	0.070
	Matched	2.38	2.00	1.67	0.095
Dummy highly cited	**Unmatched**	0.09	0.10	-0.25	0.801
	Matched	0.09	0.07	1.23	0.219
Proportion self citations	**Unmatched**	0.20	0.13	3.23	0.001
	Matched	0.20	0.12	4.13	0.000