How to capture value from linking to basic research: boundary crossing inventors and partnerships[♣]

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January 2011
First Version: October 2009

Preliminary
Work in progress

Please do not quote yet but comment

Abstract
The paper studies combinations of mechanisms through which firms connect to basic research, and how they affect various dimensions of firm's innovative performance: quality, cumulativeness and speed. 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 investigate the impact for firms of joining a partnership program with IMEC as well as the use of inventors who have "visited " IMEC. We find strong evidence that linking to IMEC has provided partner firms with more valuable technology outcomes that are appropriated better by these partner firms. Boundary crossing inventors increase the chance of developing high quality technologies. The data strongly suggest complementarity between institutional and inventor links particularly for better internal appropriation. Poaching firms without an organizational link to IMEC are less successful in using such boundary crossing inventors.

[♣] The authors wish to thank Ajay Agrawal, Dirk Czarnitzki, Lee Fleming, Alfonso Gambardella, Rahul Kapoor, Lori Rosenkopf, Bruno Van Pottelsberghe, Rosemarie and Arvids Ziedonis and the seminar participants at HBS, Wharton, Michigan, Toronto, the MOVE, Alma Graduate School Bologna, ZEW, EARIE, EPIP and REER conferences for useful comments; Andre Clerix, Johan Van Helleputte and IMEC for the collaboration and data. Bruno Cassiman is a research fellow of the SP-SP Research Center at IESE Business School and acknowledges partial financial support from the Spanish Ministry of Science and Innovation through project nº ECO2009-13169, the Catalan Government Grant nº 2009-SGR919 and Fundación Ramon Areces. Sam Arts acknowledges financial support of the Science Foundation Flanders (FWO) and OT/07/11.

1. Introduction

An important and recurrent concern in economics and management has been to understand to what extent basic research influences technological progress and ultimate economic growth. More recent evidence suggests that industrial firms are intensifying their links to basic research performed by universities and other research organizations (Cassiman, Veugelers and Van Looy, INNOS&T). In spite of these growing connections our understanding at the micro-level of the variety and distribution of these links and how they affect industrial innovation remains unclear.

In this paper we examine the links to a research organization, performing basic research and how such links affect firms' applied research productivity. We contribute to the literature in several ways. First, we move the analysis to a more disaggregate level. Firms that actively link with basic research will have a portfolio of innovative projects. It is important to examine the effect of the links on the projects exploiting such links and compare them to similar projects of firms without such links. Second, we examine the effect of various mechanisms to link across the firm boundary to basic research. Next to the decision of joining a cooperative program, we also look at the importance of boundary crossing inventors. Third, we examine several potential ways these firms might capture returns to these links to basic research: the value and quality of technologies developed, the cumulativeness of their research, or, the establishment of technology lead time.

The links to basic research that we examine focus on the links through IMEC, a world class research organization performing basic research in micro-electronics and semiconductors. IMEC has the expressed objective to bridge the gap between fundamental research done at universities and applied R&D in the industry. By financially contributing, firms can become an IMEC partner, i.e. buy "a seat at the table". As a result, they gain access to IMEC developed proprietary basic technologies. In addition, IMEC runs an industrial affiliates program where partner firms can sign up to specific research programs in their area of interest. By sending researchers to participate in the basic research program at IMEC where they interact with researchers of IMEC and other partners involved in the program, partners can acquire "a spot in the lab".[1] IMEC negotiates an elaborate IP agreement with its partners. This allows us to track through patent information the effects of affiliation to IMEC as well as the actual mobility of people and ideas.

The analysis involves comparing patents with different treatments of links to basic research at the research organization. Patents of firms that are IMEC partners are compared to patents of non-partnering firms. This allows us to trace the effect of affiliation to the research organization. In addition, we compare patents of boundary crossing inventors that have been participating in basic research programs at the research organization versus patents of inventors who did not participate in such a program. As a result we can trace the effect of cross-institutional mobility of researchers. We do this for both partnering and non-partnering firms to examine any differential effect from using an inventor link between partners and non-partners, as the latter can also poach inventors who have visited IMEC to attempt to obtain access to the basic research.

We find that firms linked to basic research through an IMEC partnership and who use boundary crossing inventors are more likely to develop higher quality innovations. Partners continue to build internally on these technologies, improving appropriation of returns in this fast paced environment. Interestingly, inventor mobility is an important link, but only when used in combination with affiliation to

[1] We thank Rosemary Ziedonis for suggesting the use of this language.

IMEC. Poaching firms without an organizational link to IMEC are less successful in using such boundary crossing inventors. This complementarity holds particularly for the quality of inventions and for building cumulativeness.

In the following section we discuss the related literature. 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 basic research and firm-level innovation outcomes is covered in a diverse literature in Economics and Management. While the economics literature mainly explores the effects of basic research on innovative performance, they provide little explanation about the processes through which basic research affects innovation. The management literature has tried to open the black box inside organizations on how basic research links effectively translate into improved innovative performance.

Any explanation of why firms engage with basic research organizations needs to argue that ultimately basic research 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 basic research know-how provides a codified form of problem-solving, it can increase the efficiency of private applied research (Arrow, 1962). In addition, basic research know-how serves as a map for technological landscapes guiding applied research in the direction of most promising technological venues avoiding thereby wasteful experimentation (Fleming and Sorenson, 2004). 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. In addition, more basic knowledge can simultaneously fertilize different research projects (Cockburn and Henderson, 1998).

Probably the most discussed argument of how actively engaging in basic research might increase applied research productivity is the fact that basic knowledge leads to a better identification, absorption and integration of external (public) knowledge (Cohen and Levinthal, 1989; Gambardella, 1995; 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).

At the same time, firms with basic research capabilities 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 basic research links might affect the inputs of the innovation process. By setting up a research friendly environment, the firm attracts researchers willing to accept a lower salary in return for the freedom to do basic research and publish their results. 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.

At the same time advances in basic research and technological advances are driven by different selection logics. Criteria for judging a new scientific contribution differ from the criteria for evaluating a new technology. For this reason science and technology are typically developed in different institutional environments, complicating the development of basic research in-house (Gittelman and Kogut, 2003). Therefore, crossing organizational boundaries seems an important requirement to access basic research knowledge with an important scientific content. Inventors with a more scientific profile are probably the most efficient bridge between these two environments. However, little empirical work has explicitly examined who these boundary spanning inventors are and how they can *effectively* bridge scientific and technology communities (Allen, 1977, Tushman & Scanlon 1981, Breschi and Catalini, 2010).

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

Probably the largest group of empirical papers have estimated a patent production function at the firm-level examining the effect of *partnerships with universities or other research organizations* on firm performance (e.g. Audretsch and Stephan, 1996; Zucker *et al* 1998; Cockburn and Henderson, 1998; Brandstetter and Sakakibara, 1998). The pre-eminence of cooperation with other entities as mechanism to access basic research is reminiscent of the importance of crossing institutional boundaries for effective knowledge transfers (Kogut and Zander, 1992; Rosenkopf and Nerkar, 2001). This holds in particular for more science based technologies (Gittleman and Kogut, 2003). The empirical evidence from these studies support the complementarity between cooperation with these research organizations and internal R&D , and find a positive effect from cooperation with universities and public research organizations on innovation productivity and sales for firms with own R&D capacity (Belderbos *et al,* 2004; Belderbos et al, 2006).

The work by Cockburn and Henderson (1998) has shown that, beyond partnerships with research institutes, also direct involvement into basic research matters. Using data on co-authorship of papers for a sample of pharmaceutical firms, they show that firms connected to basic research 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 especially in biotech, found 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 a 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 as a link to basic research. The involvement of an academic inventor in the invention team is found to lead to more valuable patents (Czarnitzki et al., 2008). Patents with references to science are found to cover 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 the technological impact of patents but that the benefits of using such links depend upon the difficulty of the inventive problem being addressed: links only appear as beneficial when researchers work with highly interdependent knowledge pieces which make the probability of discovery more uncertain and non-local search is more likely to lead to success.

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 firms hosting mobile researchers (Song, Almeida and Wu, 2003; Rosenkopf and Almeida, 2003; Singh, 2008), and even for the sender firm (Corredoira and Rosenkopf, 2010; Oettl and Agrawal, 2008). As a result, mobility across firm boundaries relates to more effective transfer of knowledge.

3. The effects of Linking to basic research: our Predictions

While the existing firm level empirical analyses typically find a positive relation between basic research activities of the firm and innovation outcomes, these analyses pay little attention to the actual micro-level mechanisms that link basic research activity to innovation performance. At the same time the invention and inventor level analyses do not clearly specify the interactions with nor control for organization level connections of the firms. They limit themselves to inventor networks without superimposing organizational structures that will affect the incentives of these inventors to develop, communicate and appropriate returns to these basic research activities.

In what follows we investigate in more detail which links matter and how. How can firms take more advantage of basic research in their applied research? How should they organize to take advantage of basic research? Where do we expect these efforts to surface? We do this for a particular case where we can carefully specify these links and their impact. Our analyses are probably most closely related to Ziedonis & Ziedonis (2005) who 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.

3.1. On mechanisms to link to basic research

Based on the literature, we hypothesize that on mechanisms to link to basic research, the spanning of organizational boundaries seems more effective to access basic knowledge advances and translate this into technological advances. Through the crossing of organizational boundaries of the right people the frictions in this knowledge transfer process can be minimized. Especially, because of the tacitness and complexity of know-how underlying leading edge research, researcher involvement and mobility should play a pivotal role. We therefore expect links involving boundary crossing inventors to be more effective. We will distinguish between these pure boundary crossing inventor links relative to more structured organization level partner links, in casu cooperative arrangements. We will also examine the interaction between firm and inventor level boundary spanning mechanisms, looking for any possible complementarity between both types of links.

3.2. On effects from links

Interactions between basic research and industry should stimulate the average quality of the applied technologies developed by interacting firms. They also are expected to lead to a higher probability of generating breakthroughs. In addition, we would expect firms to take advantage of knowledge flows that have been generated through linking across organizational boundaries by building on these knowledge flows through the internal development of new technologies This is particularly important for technologies that are based on basic research, as commercially viable technologies and products need to be developed based on these initial technologies. Not only does the link to basic research 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 might build on.

As a consequence, effects from boundary spanning firm level mechanisms and boundary crossing inventors should be reflected in the value and quality of the developed technologies generating high potential inventions. At the same time, they affect the cumulativeness of their research efforts, and, the speed at which these organizations move in technology space.

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 – a world class research institute with a mission to be a bridge between fundamental research at universities and R&D at industry.

4.1. Links to research in the micro-electronics industry

The micro-electronics industry is an interesting environment for testing effects of links with basic research. 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 research 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 (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 involvement in 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.[2]

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. 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

2 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.

technological fields. It possesses a rare combination of know how in chip design, packaging and production.

IMEC has developed a unique business model which stimulates the interactions of researchers in order to facilitate cross-fertilization of ideas among all participating scientific and industrial researchers. To this end, it runs an Industrial Affiliation Program (IIAP).

4.3. IMEC Industrial Affiliation Program (IIAP)

IMEC's Industrial Affiliation Program (IIAP) is designed to create an innovation model in which participating companies share costs, risks, human resources and intellectual property while engaging in collaborative R&D on generic technologies. 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 can send 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, focused at 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).[3] 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.

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, 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

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

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,[4] 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 but not on IMEC payroll at the time of patent application. We name these inventors "boundary crossing" inventors as they have been active in the generation of IP at IMEC at some point in their career, without being an IMEC employee. 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.[5]

[4] These patents include EPO, USPTO and PCT patent applications
[5] The use of detailed personnel data obtained from IMEC for all inventors in our sample allows us to identify the affiliation of an inventor at a particular moment in time, differentiating IMEC and non-IMEC employees at the time of patenting. 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

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 used consists of 1,089 USPTO patents, 1,835 unique inventors and 87 companies.[6] Figure 1 provides a visual description of the final sample construction. The sample can be divided between 221 company-owned patents which mention at least one boundary crossing IMEC affiliated researcher employed by the assignee company 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 crossing IMEC visiting researcher as inventor, 45 patents assigned to non-partner firms but having a boundary crossing 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 "a seat at the table" and having "a spot in the lab" at IMEC.

Insert Figure 1 here

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

matches (type II error). Given our objective to trace inventor interaction and mobility, this conservative approach seems most appropriate.

[6] 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 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).

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

In addition, we define four new categories:

- **Crossing-Partner** patents are patents assigned to an IMEC partner organization (i.e. a member of its IIAP Program) and developed by a boundary crossing inventor, i.e. an inventor that has been active in the generation of IP at IMEC at some point earlier in his career.
- **Citing-Partner** patents are patents assigned to IMEC partners citing R0-R1 patents, but without being developed by a boundary crossing inventor.
- **Crossing-NonPartner** patents are patents assigned to non-partner companies, but that have a boundary crossing inventor as an inventor on the patent.
- **Citing-NonPartner** patents are patents assigned to non-partner companies, 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 crossing inventors and/or firm partnerships at the invention (patent) level. The strongest link is a combination of boundary crossing inventors and organizational-level links, as is the case for *Crossing-Partner* patents. Patents that only have an organizational-level link with the research center are *Citing-Partner* patents, while *Crossing-NonPartner* patents are patents with only an inventor link to

IMEC. These are most likely poaching cases whereby a non-partner company hires away an affiliated or visiting researcher. Finally, *Citing-NonPartner* 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 (base case) for comparison with our various link-categories. 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 only for identifying patents that are related in technology space.

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 crossing inventor and/or partnership links with IMEC, using the *Citing-NonPartner* patents as the base case, we can estimate the impact of different links and their interactions. In terms of impact, we consider various outcome dimensions.

5.2.1. *Quality of Innovation*

To evaluate the effect of linking to basic research through IMEC on the technological impact and the economic value of an organization's patents, we employ a commonly used indicator in past studies to measure 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.

Given that the value distribution of inventions is extremely skewed with a small fraction of all inventions contributing disproportionally to company performance, we also develop a measure of high impact or breakthrough invention. To calculate a measure of technology breakthrough, the mean and standard deviation of forward citation count are calculated for all US patents within the same 3 digit technology class application year group. A patent is labeled as breakthrough in case the count of forward citations is larger than the mean plus 2 times the standard deviation in their respective groups (see Fleming and Arts, 2011).

In line with our hypotheses developed in section 3, we expect a positive correlation between boundary spanning links and forward citations, i.e. Crossing and/or Partner patents are expected to have a higher rate of forward citations and a higher probability of breakthroughs as compared to the base case of *Citing-NonPartner* patents.

V(Crossing-Partner), V(Citing-Partner), V(Crossing-NonPartner) > V (Citing-NonPartner) (V1)

Comparing *Crossing-Partner* patents with *Citing-Partner* patents would test for the additional effect of a boundary crossing inventor link for partner firms. Comparing

Crossing-Partner with *Crossing-NonPartner* patents would test for the additional effect of an institutional partner link for firms using a boundary crossing inventor link:

V(Crossing-Partner) > V(Citing-Partner) (V2.1)

V(Crossing-Partner) > V(Crossing-NonPartner) (V2.2)

V2.1 and V2.2 each test a part of a complementary relationship between institutional and inventor links. If inventor and organizational links would be fully 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 *Crossing-Partner* patents outperforming BOTH *Citing-Partner* and *Crossing-NonPartners* all relative to *Citing Non-Partners* patents.

V(Crossing-Partner) + V (Citing-NonPartner) > V(Citing-Partner) + V(Crossing-NonPartner) (V3)

5.2.1.1. 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, Jaffe & Trajtenberg 2002).

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.

C(Crossing-Partner), C(Citing-Partner), C(Crossing-NonPartner) > C (Citing-NonPartner) (C1)

Comparing *Crossing-Partners* with resp *Citing-Partners* and *Crossing-NonPartners*, tests for the additional effects of resp. the inventor and the institutional link :

C(Crossing-Partner) > C(Citing-Partner); (C2.1)

C(Crossing-Partner) > C(Crossing-NonPartner); (C2.2)

We particularly expect the link through boundary spanning inventors should improve cumulativeness (C2.1). If inventor and organizational links are complementary, i.e. boundary spanning inventor links are more effective for affiliated partners and/or affiliated partners can build cumulativeness better with boundary spanning inventor links, we have:

C(Crossing-Partner) + C (Citing-NonPartner) > C(Citing-Partner) + C (Crossing-NonPartner) (C3)

5.2.1.2. 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 basic 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.

LT(Crossing-Partner), LT(Citing-Partner), LT(Crossing-NonPartner) > LT (Citing-NonPartner) (LT1)

Comparing *Crossing-Partners* with resp *Citing-Partners* and *Crossing-NonPartners*, tests for the additional effects of resp the inventor and the institutional link. Again we expect particularly the link through crossing inventors to improve lead time:

LT(Crossing-Partner) > LT(Citing-Partner); (LT2.1)

LT(Crossing-Partner) > LT(Crossing-NonPartner); (LT2.1)

And if inventor and organizational links are complementary, *Crossing-Partner* patents will outperform in terms of Lead Time both *Citing-Partner* and *Crossing-NonPartner* patents, all relative to the base case of *Citing-NonPartner.*

LT(Crossing-Partner)+LT(Citing-NonPartner) > LT(Citing-Partner)+LT (Crossing-NonPartner) (LT3)

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 and for truncation by including *application year* dummies.

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.

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 <u>inventor</u> 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 <u>firm level</u> 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.[7] 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.[8]

Insert TABLE 3 & 4 here

5.3. Econometric Methodology

5.3.1. 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

[7] These firm-level variables vary across different patents of the same company applied for at different moments in time.
[8] Note that their interpretation of self citations does not 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.

mean is correctly specified (Gouriéroux et al., 1984). We also 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). To estimate the likelihood of breakthrough or high impact inventions we use Probit models.

5.3.2. 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.

5.3.3. Technological Lead Time

To estimate the speed at which research teams with different inventor- and organizational-level links with IMEC assimilate IMEC's prior art and develop subsequent inventions built on this prior art, we use forward citation lags, i.e. the lag in years between the application 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. (TO BE COMPLETED)

5.4. Partner and Inventor Selection Issues

We need to address potential selection issues at the level of the partner firm and inventor. One could argue that firms which expect to get more out of a partnership with IMEC are more likely to become a partner in the first place. To formally control for a partner selection issue, we estimate the probability of a particular patent to be from an affiliate partner at a particular moment in time in function of patent characteristics, a company's core technological area (8 categories), 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. 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 *Crossing-Partners* and *Citing-Partners* patents with *Crossing-NonPartners* and *Citing-NonPartners* patents.

Beyond the partner selection issue, there might also be an inventor selection issue in case firms would send their more competent or less 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 partners with regular evaluations of the affiliate researchers in the IMEC teams. We attempt to check 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,[9] suggesting that there is no obvious inventor selection issue.[10]

6. Results

6.1. 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) have fewer backward citations (patent references) and are more likely to cite the scientific literature (non-patent reference binary), confirming the more "basic"

[9] 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.

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

scientific 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 institute.

Insert TABLE 3&4 here

When we look at the company patents, we see that *Crossing-Partner* patents, which have both a boundary crossing inventor and an institutional partner 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 are also most likely to be a "break-through" patent. *Citing-Partner* patents with only an institutional partner link to IMEC, but without the boundary crossing inventor link, are as likely as *Crossing-Partner* patents to receive forward citations, but the count of these citations are lower, and the probability of being a "break-through" patent is also significantly lower.[11]

Both *Crossing-Partner* and *Citing-Partner* 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[12].

Contrary to our expectation, however, especially given the strategic importance of technology lead time in the industry, we do not find that patents with boundary crossing inventors and/or organizational partnership links with IMEC have shorter citation lags.

In summary, these first descriptive results already indicate that the tighter the link with IMEC, the more able a company seems to assimilate the knowledge

[11] Ttest on difference of means *Crossing-Partner vs Citing-Partner:* count forward citations within 3 year: t=3.8318***; highly cited: t=2.5764***
[12] Ttest on difference of means *Crossing-Partner vs Crossing-NonPartners:t=2.9842***; Citing-Partner vs Citing-NonPartners:t=3.2297****

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 visiting the research center in order to collaborate with other industrial and scientific researchers in joint R&D projects – i.e. boundary crossing inventors – seem to play a decisive role as link between industry and IMEC, but most importantly when they are associated with firms that have an institutional partnership link with IMEC. These descriptive statistics, although not controlling for other factors, are already supportive for the positive impact of IMEC links for firms' technology development, particularly the combined inventor and partner link.

6.2. Multivariate analysis: Quality of Innovation

Table 5 shows the results of our count model estimations. *Crossing-Partner* patents receive between 46% and 94% more citations compared to the control group of *Citing-NonPartner* patents. For firms that are not IMEC affiliated partners, patents developed with the assistance of boundary crossing inventors, are not more valuable compared to patents developed without the assistance from boundary crossing inventors. Our expectation that boundary crossing inventors are a pivotal mechanism for linking therefore only seems to hold for firms that also have a boundary crossing link at the institutional level. All these results are supportive for complementarity between organizational and inventor boundary spanning mechanisms. The formal test for complementarity (Chisq-test on V3) is significant at 7% for the fixed citation window results.

The combination of the low (and insignificant) coefficient for *Crossing-NonPartner* patents and the minimal difference between the coefficients of *Crossing-Partner* and *Citing-Partner* patents[13] are not supportive of our hypotheses that when comparing the organizational and the inventor link, the inventor link is the strongest and can generate the most extra value.

Insert TABLE 5 here

On breakthroughs, *crossing-Partner* patents seem more likely to have a high impact across all models. When correcting for company and inventor characteristics, this higher probability of a high impact patent seems to hold not only for *Crossing-Partner* patents, but for all patents with partner and/or inventor links .

Insert TABLE 6 here

6.3. 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 both *Crossing-Partner* and *Citing-Partner* 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 0.0624 to 0.1064[14] larger proportion of self citations relative to comparable patents by non-affiliates (Table 6). Although we find that partner patents with a boundary crossing inventor link have a larger proportion of self citations compared to patents of affiliate partners without a boundary crossing

[13] The formal test of V2.1 is only significant at 13%, while the test for V2.2 is significant at 3.7%
[14] Marginal effects in OLS regressions

inventor link, this difference is not statistically significant (C2.1). There is hence no evidence of significantly higher effects from the inventor link.

A patent from a non-partnering firm but with a boundary spanning inventor link has a significantly smaller proportion of self citations compared to similar patents of partner companies (C2.2). 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, if there is no institutional link with IMEC. Being able to fully exploit the researcher mobility link seems to require a complementary institutional link.

All these findings are supportive of 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 as to capitalize and appropriate returns to the R&D investment through the internal development of the next generation of technologies. The test for complementarity (Chisq-test on C.3) indeed is statistically significant at the 1% level.

Insert TABLE 7 here

6.4. Technological Lead Time

We argued that lead time of innovation projects are increasingly a differentiator in the micro-electronics business because of the relentless shortening of product life cycles. Unfortunately, our descriptive statistics do not seem to support this prediction (Table 8).

6.5. Partner selection

While the empirical results are supportive for the tangible effects of links with IMEC, particularly for the combination of inventor and organizational spanning mechanisms, we need to address potential selection issues at the level of the partner firm and the inventor.

To formally control for a partner selection issue, we estimated the probability of a particular patent to be an affiliate partner at a particular moment in time. The selection model (not reported) results in a pseudo R^2 of 0.45 and we make 82% correct predictions[15]. Consequently, we calculate the propensity scores to be a partner patent and use kernel matching to compare *Crossing-Partners* and *Citing-Partners* patents with *Citing-NonPartners* patents, which is our bench-mark case (hypotheses 1). We also compare *Crossing-Partners* to *Crossing-NonPartners* to test our hypotheses on the extra value added from an institutional link (hypotheses 2.2). The matched sample procedure does not allow testing for an extra effect from an inventor link (hypotheses 2.1) nor for full complementarity between both types of links (hypotheses 3). Results are presented in Table 9.

Insert TABLE 9 here

The matched patents reveal a similar story as from our regressions with some interesting nuances. Compared to the benchmark case of *Citing-NonPartner* patents, the superior performance of *Crossing-Partner patents* is confirmed: boundary crossing inventors of affiliate partners matter for the quality of the technologies developed as shown for the forward citations and the self-citation rate. The effect of an institutional link only, i.e. comparing *Citing-Partner* patents to *Citing-NonPartner* patents, shows significant positive effects on self-cites. The results from comparing *Crossing-Partners* to *Crossing-NonPartners*, i.e. the additional effect of partnership for inventor links, confirms a significantly higher effects from Crossing-Partners patents on average quality as well as on the likelihood of high impact. On self cites,

[15]The constant only model would correctly assign 56% of the patents.

we find that patents of crossing inventors of affiliate partners score significantly higher as compared to matched patents from crossing inventors of non-partners, thus confirming the importance of an organizational link to exploit the advantages of an inventor link

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. Overall, we therefore conclude that institutionally linking to IMEC has provided some tangible benefits for IMEC partners.

We have found that the boundary crossing inventor link, 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 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 crossing inventor links are significantly stronger 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. Boundary crossing inventor links do not tell the whole story. Their effectiveness is contingent on an organizational crossing link. An organizational crossing link with IMEC is what matters most. Firms need to buy a seat at the table before a spot in the lab can have any effect.

Although the results confirm an overall positive effect on innovative performance from linking to basic science, they are also highly supportive of the paper's research strategy to differentiate among the linking mechanisms as well as the impact dimensions considered. At the same time they also suggest important avenues for further research. First, the analysis should extend the set of linking mechanisms (e.g. co-publications). Secondly, more information on how firms organize internally for effective linking from case studies at partnering and non-partnering firms would be helpful to further fine tune the search for institutional controls on the effects and the partner selection analysis. Particularly critical company characteristics beyond the scale and scope of R&D and the age of a company need to be factored in to explain appropriation success. Thirdly, in order to better understand what makes the IMEC model so successful, a more indepth study of IMEC is in order. As IMEC is not characterized by major regime shifts over time which would allow to pinpoint critical characteristics for success, comparing with other research consortia formula, is a more promising avenue to understand what makes IMEC special. Sematech and MCC for instance, are alternatively consortia models in semiconductors which differ sufficiently in terms of IP model, public and private funding, collaboration model as well as in success (Ziedonis & Ziedonis (2005)) to make for a fruitful comparison analysis.

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Figure 1: Final Sample Construction

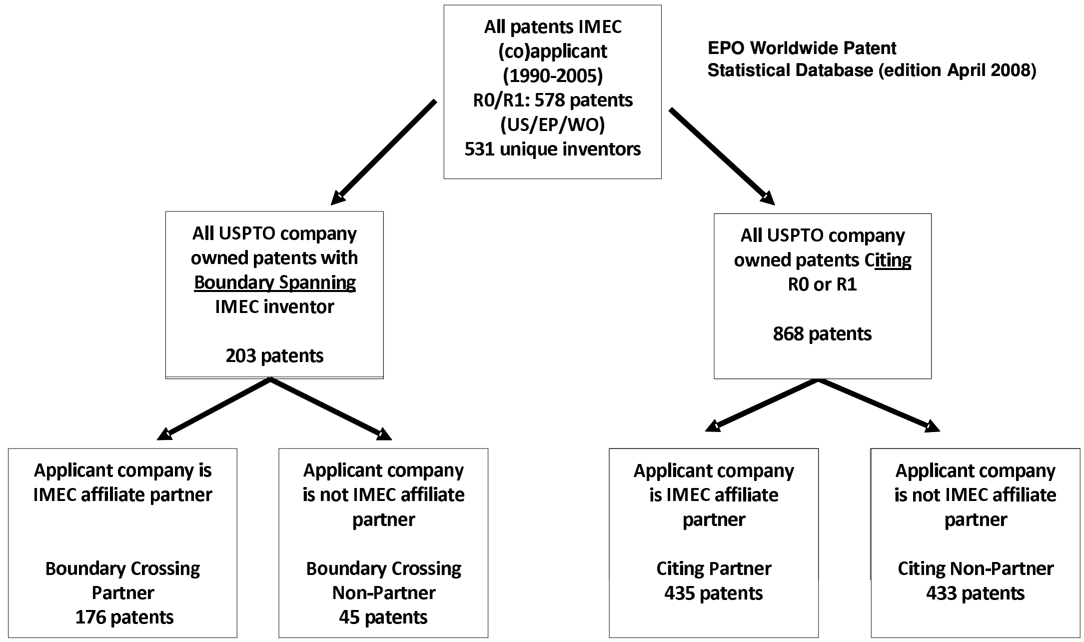

Figure 2: Classification of Patents

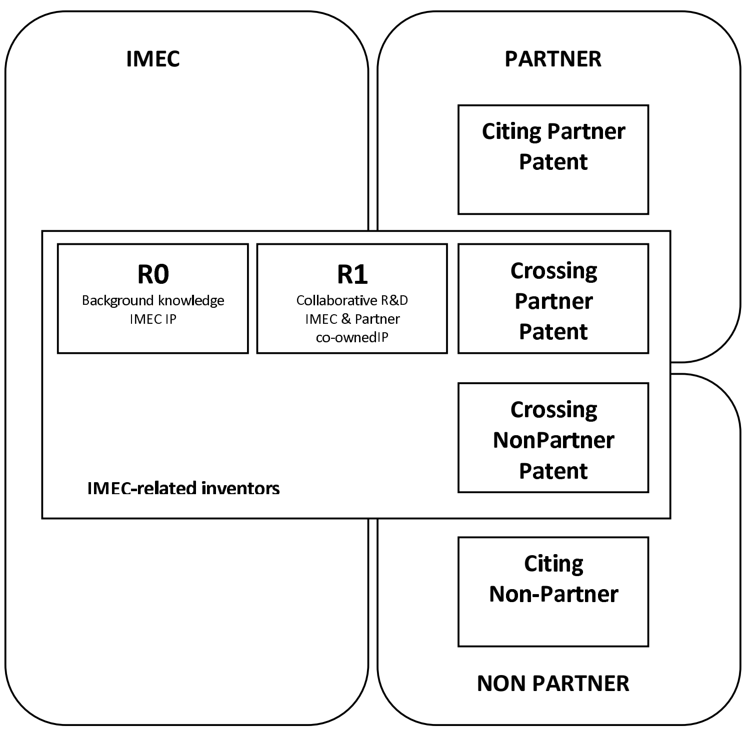

TABLE 1: Patents by Technology Field

	IMEC		IMEC PARTNER		NON-IMEC PARTNER	
FIELD	R0	R1	BOUNDARY CROSSING INVENTOR	NO BOUNDARY CROSSING INVENTOR	BOUNDARY CROSSING INVENTOR	NO BOUNDARY CROSSING 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	Crossing Partner Patent	Citing Partner Patent	Crossing NonPartner Patent	Citing Non-Partner Patent
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	Med	Std Dv	Min	Max
Count forward citations	The number of times a patent is cited as prior art by subsequent patents	1089	5.31	2	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	1	5.17	0	61
Forward citations binary	Dummy indicating whether a patent received citation(s)	1089	0.69	1	0.46	0	1
High impact Invention binary	Dummy indicating whether the patent receives more forward citations than the mean+2*StDev of the number of forward citations in the same technology class application year group		0.05	0	0.22	0	1
Count forward self citations	The number of times a patent is cited by patents assigned to the same company	1089	1.31	0	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	0	2.23	0	27
Proportion forward self citations	The number of self citations divided by total amount of forward citations	1089	0.17	0	0.31	0	1
Forward self citations binary	Dummy indicating whether a patent received self citation(s)	1089	0.32	0	0.47	0	1
Patent scope / Count IPCs	The number of IPC codes	1089	2.58	2	2.07	1	14
Count non-patent references (NPRS)	The number of non-patent citations	1089	7.76	2	15.53	0	99
Count patent references (PRS)	The number of patents cited by the patent	1089	30.41	18	31.43	0	147
Count inventors	The number of inventors on the patent	1089	2.94	2	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	0.02	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	3.34	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	0.96	1.16	0	5
Age company	The number of years since the company's first patent	1089	50.92	52	28.19	4	109

TABLE 4: Descriptive Statistics by Patent Type

	IMEC				IMEC PARTNER				NOT IMEC-PARTNER			
	R0		R1		BOUNDARY CROSSING INVENTOR		CITING		BOUNDARY CROSSING INVENTOR		CITING	
	Avg	Med	Avg	Med	Avg	Med	Avg	Med	Avg	Med	Avg	Med
Count forward citations	7.32	3	7.67	2	7.16	2	4.40	1	5.13	1	5.48	2
Count forward citations within 3 y	3.05	2	4.15	1	4.41	1	2.38	1	1.64	1	2.86	2
Forward citations binary	0.78	1	0.67	1	0.65	1	0.66	1	0.56	1	0.76	1
High impact Invention binary	0.07	0	0.14	0	0.09	0	0.04	0	0.07	0	0.04	0
Count forward self citations	0.67	0	1.33	0	2.46	0	1.40	0	0.24	0	0.87	0
Count forward self citations within 3 y	0.27	0	0.70	0	1.28	0	0.90	0	0.11	0	0.61	0
Proportion forward self citations	0.12	0	0.15	0	0.21	0	0.20	0	0.05	0	0.13	0
Forward self citations binary	0.29	0	0.30	0	0.36	0	0.35	0	0.13	0	0.31	0
Citation lag R0/R1 cited					5.34		5.34		6.01		5.26	

TABLE 5: Count Forward Patent Citations as Dependent Variable

	Poisson Quasi Maximum Likelihood			Generalized Negative binomial	Zero-inflated Negative binomial		Poisson Count forward citations within 3 years
	(1)	(2)	(3)	(4)	(5) Count	(6) Logit	(7)
CROSSING PARTNER	0.6612	0.5501*	0.5325*	0.3822*	0.3764*	3.6165**	0.4754*
	[0.504]	[0.324]	[0.298]	[0.230]	[0.223]	[1.417]	[0.281]
CITING-PARTNER	-0.0622	0.0339	0.0718	0.0623	0.0456	1.4179	0.0512
	[0.169]	[0.120]	[0.129]	[0.127]	[0.130]	[1.095]	[0.150]
CROSSING NON-PARTNER	0.2264	0.2856	0.2861	0.0851	0.2326	6.7260	-0.2385
	[0.267]	[0.263]	[0.285]	[0.313]	[0.381]	[6.866]	[0.262]
PATENT CHARACERISTICS							
Count IPCs		0.1368***	0.1296***	0.1093***	0.1026***	-2.5300	0.1310***
		[0.019]	[0.020]	[0.028]	[0.023]	[2.089]	[0.017]
NPRS		0.0141***	0.0132***	0.0147***	0.0133***	0.0481	0.0113***
		[0.003]	[0.003]	[0.004]	[0.004]	[0.076]	[0.004]
PRS		-0.0024	-0.0029	0.0007	0.0001	0.0090	-0.0009
		[0.003]	[0.003]	[0.003]	[0.003]	[0.073]	[0.003]
Count inventors		-0.0198	-0.0198	-0.0206	0.0014	0.8161	0.0004
		[0.027]	[0.023]	[0.023]	[0.025]	[0.781]	[0.021]
INVENTOR CHARACTERISTICS							
Inventor experience			0.2285	0.2528	-0.0068	-30.8852	0.1887
			[0.385]	[0.406]	[0.374]	[25.009]	[0.361]
FIRM CHARACTERISTICS							
Scale			0.0160	0.0279*	0.0193	-0.5740	0.0336*
			[0.019]	[0.016]	[0.017]	[0.689]	[0.020]
Scope			-0.0441	-0.0713	-0.0941*	1.0905	-0.1414*
			[0.079]	[0.062]	[0.055]	[2.079]	[0.073]
Age company			-0.0066**	-0.0059**	-0.0051*	0.0555	-0.0075***
			[0.003]	[0.002]	[0.003]	[0.058]	[0.003]
Constant	1.1066***	1.1308***	1.7725***	1.3016***	1.2882***	-6.1110	-13.8818
	[0.294]	[0.266]	[0.336]	[0.309]	[0.357]	[73.522]	[16.604]
Test of joint significance							
Technology class	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***
Application year	Incl.***	Incl.***	Incl.***	Incl.***	Incl.***	Incl.	Incl.
Overdispersion parameter				***	0.0759		
					[0.078]		
Vuong test					5.66***		
Log LH/PLH	-5123.8528	-4676.4399	-4605.1141	-2533.882	-2515.2096		-3017.1495
Observations	1089	1089	1089	1089	1089	1089	1089
(Pseudo) R-squared	0.308	0.368	0.378	0.073	0.113		0.231

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

Robust standard errors in brackets, clustered by firm, application year and technology class dummies are used to model the variance term in the gnbreg model

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

Marginal Effects (3): *Crossing-Partner* 70%*; Citing-*Partner* 7%; *Crossing-NoPartner* 33%

(7)C2.1: chi2(1)= 2.20; C2.2: chi2(1)= 4.35; C2.2: z= 1.8***

TABLE 6: Dummy High Impact Invention as Dependent Variable

	Marginal Effects after Probit		
	(1)	(2)	(3)
CROSSING PARTNER	0.0604*	0.0568**	0.0503***
	[0.036]	[0.024]	[0.018]
CITING-PARTNER	-0.0035	0.0055	0.0453**
	[0.024]	[0.021]	[0.021]
CROSSING NON-PARTNER	0.0434	0.0457	0.0571*
	[0.032]	[0.030]	[0.034]
PATENT CHARACERISTICS			
Count IPCs		0.0128***	0.0109***
		[0.003]	[0.002]
NPRS		0.0006*	0.0003
		[0.000]	[0.000]
PRS		-0.0000	-0.0001
		[0.000]	[0.000]
Count inventors		-0.0036	-0.0025
		[0.003]	[0.003]
INVENTOR CHARACTERISTICS			
Inventor experience			0.0437
			[0.044]
FIRM CHARACTERISTICS			
Scale			-0.0140**
			[0.006]
Scope			0.0093
			[0.011]
Age company			-0.0006**
			[0.000]
Test of joint significance			
Technology class	Incl.***	Incl.***	Incl.***
Application year	Incl.***	Incl.***	Incl.***
Log PLH	-176.63411	-165.82557	-150.40797
Observations	961	961	961
(Pseudo) R-squared	0.162	0.213	0.286

All regressions include application year, technology dummies, R5 is control group
Robust standard errors in brackets, clustered by firm,
*** p<0.01, ** p<0.05, * p<0.1
(3)C2.1: chi2(1)= 0.05; C2.2: chi2(1)= 0.04; C2.2: z= -1.29

TABLE 7: Proportion Self Citations as Dependent Variable

	OLS			HETORSKEDASTIC TOBIT		
	(1)	(2)	(3)	(4)	(5)	(6)
CROSSING PARTNER	0.0784**	0.1064***	0.1050***	0.2184*	0.3538***	0.3297***
	[0.0306]	[0.0255]	[0.0256]	[0.118]	[0.093]	[0.089]
CITING PARTNER	0.0666*	0.0624*	0.0680*	0.1672	0.1587	0.2071*
	[0.0391]	[0.0355]	[0.0394]	[0.125]	[0.104]	[0.108]
CROSSING NON-PARTNER	-0.0566*	-0.0379	-0.0358	-0.5689***	-0.4767**	-0.4487**
	[0.0338]	[0.0365]	[0.0378]	[0.202]	[0.202]	[0.197]
PATENT CHARACERISTICS						
Count IPCs		0.0009	0.0013		0.0097	0.0091
		[0.0050]	[0.0050]		[0.014]	[0.014]
NPRS		0.0012	0.0010		0.0039	0.0033
		[0.0012]	[0.0012]		[0.003]	[0.003]
PRS		0.0014**	0.0014**		0.0055***	0.0051***
		[0.0007]	[0.0006]		[0.002]	[0.002]
Count inventors		-0.0045	-0.0033		-0.0068	0.0014
		[0.0050]	[0.0047]		[0.016]	[0.016]
Count for citations	0.0029***	0.0024***	0.0023***	0.0148***	0.0124***	0.0114***
	[0.0008]	[0.0009]	[0.0008]	[0.004]	[0.004]	[0.004]
INVENTOR CHARACTERISTICS						
Inventor experience			-0.0197			-0.1439
			[0.1285]			[0.548]
FIRM CHARACTERISTICS						
Scale			0.0044			0.0127
			[0.0036]			[0.021]
Scope			-0.0252*			-0.1181*
			[0.0150]			[0.066]
Age company			-0.0001			-0.0011
			[0.0005]			[0.002]
Constant	-0.0019	-0.0215	0.0121	-6.2267	-6.7872	-5.8318
	[0.0454]	[0.0462]	[0.0622]	[14.334]	[108.153]	[9.436]
Test of joint significance						
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				8.34*	16.80***	18.04***
Log PLH				-752.902	-731.998	-727.835
Observations	1089	1089	1089	1089	1089	1089
(Pseudo) R-squared	0.097	0.126	0.130	0.107	0.131	0.136

All regressions include application year 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): *Crossing-Partner* 34%***, *Citing-Partner* 29%***, *CitingNonPartner* -3%
(6)C2.1: chi2(1)= 0.34; C2.2: chi2(1)= 0.00***; C2.2: z= 2.54**

TABLE 8: Citation Lag R0/R1 Cited

TO BE COMPLETED

TABLE 9: Matched Partner/Non-Partner Patents: Nearest neigbor

		PARTNER (TREATED)	NON-PARTNER (NON-TREATED)	t	TTEST P>ltl
	CROSSING PARTNER vs CITING NON-PARTNER				
Count forward cit 3y	**Unmatched**	4.41	2.86	2.88	0.00
	Matched	4.57	1.40	4.25	0.00
High Impact	**Unmatched**	0.09	0.04	2.27	0.02
	Matched	0.09	0.01	3.52	0.00
Proportion self citations	**Unmatched**	0.21	0.13	2.96	0.00
	Matched	0.21	0.04	5.99	0.00
Citation lag	**Unmatched**				
	Matched				
	CITING PARTNER vs CITING NON-PARTNER				
orward cit 3y	**Unmatched**	2.38	2.86	-1.81	0.07
	Matched	2.47	2.49	-0.07	0.94
ıpact	**Unmatched**	0.04	0.04	-0.35	0.72
	Matched	0.04	0.05	-0.53	0.60
:ion self citations	**Unmatched**	0.20	0.13	3.23	0.00
	Matched	0.20	0.07	6.74	0.00
ı lag	**Unmatched**				
	Matched				
	CROSSING PARTNER vs CROSSING NON-PARTNER				
orward cit 3y	**Unmatched**	4.41	1.64	1.97	0.05
	Matched	5.39	1.69	3.91	0.00
ıpact	**Unmatched**	0.09	0.07	0.52	0.61
	Matched	0.11	0.04	2.06	0.04
:ion self citations	**Unmatched**	0.21	0.05	2.98	0.00
	Matched	0.24	0.18	1.73	0.09
ı lag	**Unmatched**				
	Matched				