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Fuel on the Invention Funnel: Technology Licensing-in, Antecedents and Invention Performance

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Abstract:
In this paper, we examine the impact of technology licensing-in on firm invention performance. Studying a sample of 266 licensees and matched non-licensees using a two-part model specification, we find that licensees are more likely to introduce inventions than their non-licensee counterparts. This holds both if we consider invention in general, and invention in the licensed technological class only. We also show that familiarity with the licensed technology and technological specialization drives licensees to pursue a narrow invention strategy primarily focusing on the technological class specified in the license agreement.

Keywords: Licensing-in, Invention, Dynamic Capabilities, Learning Opportunities, Technological familiarity, Technological specialization

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INTRODUCTION

Technology licensing is becoming an increasingly popular instrument for firms to tap into other organizations' research outcomes. External knowledge licensing gives firms access to technologies that help to fill gaps, reveal blind spots (Chesbrough 2003), and complement internal capabilities, enhancing a firm's development over time (Tsai and Wang 2007). That firms license in technologies directly goes against what Katz and Allen (1982) referred to as the "not invented here" syndrome. Licensing-in indeed indicates that firms do not suffer from this syndrome by embraces the inventiveness of external agents. However, despite increasing anecdotal evidence,[1] the potential of licensing-in in terms of fuelling firms' innovation funnel has been poorly acknowledged (Chesbrough 2003).

Technology licensing has enhanced inter-connectivity, propelled knowledge dispersion, reduced the costs of accessing potentially valuable external knowledge and, thus, produced new possibilities for accessing and using the knowledge residing in other firms, communities, and external individuals (Chesbrough 2003; Granstrand et al. 1992; Narula 2001). While this opens up new opportunities to enable continuous matching of strategic industry factors with a wider set of resources, it also poses new challenges for management in terms of efficient integration, combination, and exploitation of internal and external knowledge (Cassiman and Veugelers 2006).

The literature on licensing enhances our understanding of the determinants and conditions favoring the decision to license-out (e.g. Fosfuri 2006; Kim and Vonortas 2006). However, to our knowledge, the strategic and economic rationales for licensing-in practices have not been explored. Also, the role played by licensing-in as a principal component of the firm's invention strategy has generally been overlooked. An exception is the work by Tsai and Wang (2007: 152) who suggest that "by inward technology licensing, the firm may accumulate its technological knowledge and strengthen its technological capabilities from the search and use of external technology". They investigate firm performance, showing that firms that enter into licensing agreements as licensees, and combine this with internal research and development (R&D) activities, show high value added. Their study underscores the importance of exploring the role of licensing as a promoter of firm invention performance. There is a clear need for studying how licensing shapes organizations and their performance.

[1] There are several business examples that point to this trend. For instance, in 2004, PPOL Inc., a California-based holding company that sells proprietary multi-functional telecommunications equipment and runs the on-line network service, Pan Pacific Online, announced its new growth strategy focused on in-licensing of proven and promising technologies. According to the Chairman and Chief Executive Officer "this growth strategy leverages our significant technology expertise and robust core business in Japan to maximize shareholder value" (see Form 8K, ex-99.1 "Miscellaneous Exhibit" filed on 2nd April 2004, available online at http://www.secinfo.com/d11MXs.1965.d.htm, accessed January 2008.)

Building on the previous insights, this paper explores the extent to which licensing-in influences the licensee's inventive performance *ex post*. Drawing on the Open Innovation Approach and the Dynamic Capabilities Perspective – which together provide a framework for understanding competitive advantage as being based on the joint exploitation and creation of internal and external firm-specific capabilities (Chesbrough 2006; Teece 2008; Teece et al. 1997) – we test empirically for whether licensing-in of external technologies impacts on the firm's rate of inventiveness. Our argument is that licensing-in enables knowledge re-combination and the development of dynamic capabilities and absorptive capacity, producing novel technological advances. The overall findings from our econometric analysis suggest that there is a *licensing-effect* that empowers the inventive endeavors of licensees. The effect is twofold. First, licensing increases the chances and extent of invention in general. Second, licensing promotes spill-over and learning effects that are beneficial to firm's invention activities related to the technological class specified in the license agreement. Additionally, our analysis indicates that particular characteristics of licensees act as antecedents causing them to adopt a narrowly defined invention pattern specified by the licensed technology. Specifically, licensees that are technologically specialized and familiar with the licensed patents center their technological achievements around the technological classes included in the license agreement.

The paper is organized as follows. The next section develops the hypotheses, building on insights from the literature on licensing, re-interpreted through the lens of the open innovation approach and the dynamic capabilities perspective. This is followed by a method and data section that describes in depth the matching procedure adopted to develop the control sample of non-licensees. We present our dataset of 266 observations, including 133 licensee firms (treatment sample) and 133 non-licensing firms (control sample) and discuss the econometric techniques employed. In the results section we present our findings. The paper concludes by discussing the findings and implications of these new insights on theory and practice and providing some suggestions for further research.

HYPOTHESES

The purpose of this research is to show how technology licensing steers the invention performance of firms. Firms have several motives for acquiring technologies from other firms (see e.g. Lubatkin 1983). Yet, the technology licensing literature argues that licensing is a mechanism employed to get rapid access to a proven/mature technology while reducing firms' financial exposure and *time-to-market* (Atuahene-Gima 1993; Chatterji 1996; Roberts and Berry 1985). In fact, licensing-in is traditionally considered a reaction to a technological shortfall in the licensee (Lowe and Taylor 1998). In other words, licensing-in generally has been seen as a firm's tactical response to technological shortcomings. However, licensing-in can also be perceived as a way of fostering technological learning - for instance, in the form of new patents (Johnson 2002) - by exploiting and developing the licensed technology over time. Indeed, licensing-in can be considered an extension of the licensee's R&D activities that guarantees the technological reliability of a technical advance, achieved by a third party. From this perspective, licensing-in should be seen as integral to a firm's invention activities rather than a decision to outsource part of its R&D efforts.

The idea that licensing creates potential learning opportunities is well recognized in the literature on technology transfer from developed to developing countries (e.g. Prahalad and Hamel 1990). The capacity and predisposition of receiving nations to absorb technological knowledge from the outside are principal drivers of this type of learning. In order to benefit, recipients need "technological leverage" capabilities that allow them "to combine disparate sources in sequential process of organizational learning" (Mathews and Cho 1999). Along similar lines, Johnson (2002) investigates the effect of licensing activities - past and current – on the rate of patenting in the Brazilian national system. His findings – which are at the aggregate level - are intuitive, and suggest that licensees learn "about a technology during the licensing period, possibly even developing new patentable technology during the license" (Johnson 2002: 175). Thus, he introduces the concept of *learning-by-licensing,* capturing the alleged positive effects of licensing on the patenting activity and productivity of the licensee.

Investigating Japanese and English technology licensing at firm-level, Pitkethly (2001) warns about the threat to licensors of incautious licensing-out of technology to competitors. He emphasizes that licensees may learn from the licensed technology, eventually to the detriment of the licensors' technological lead, providing support for the relevance of *learning opportunities* represented by license agreements. License agreements have been argued to be much more than the simple transfer of technology from one firm to another (Anand and Khanna 2000; Bessy et al. 2002). The license agreement acts as an instrument that the parties can employ to open up a channel through which information and knowledge, either voluntarily or inadvertently, can flow, thus providing information beyond what is described in the transmitted (patented) documents and creating room for purposeful and accidental learning.

License to Invent

Rothaermel and Deeds (2004) emphasize that strategic alliances may be motivated by both exploration and exploitation. In their investigation of a sample of biotechnology firms, they promote licensing, in particular, as an exploitation strategy. Firms enter into license agreements in order to bring already existing technological achievements through clinical trials, and eventually introduce them onto the market. Broadly speaking, considering organizations as problem-solving entities engaging in search and discovery (Cyert and March 1963; March and Simon 1958), technology licensing becomes an integrated search strategy, which involves the licensee exploring new areas of the technological landscape for new inventions by combining internal knowledge with the licensed technology. In this sense, the licensed technology can be regarded as an additional input to the firm's invention resources becoming an additional element in the process of exploration that allows firms to depart from prior search patterns. It thereby acts as a catalyst that permits the licensee to search more broadly (Laursen et al. 2008). A broad search strategy is associated with more extensive possibilities of discovering new and potentially lucrative combinations of existing technologies (Levinthal and March 1993; March 1991). Thus, licensing-in provides the licensee with positive externalities beneficial to the firm's invention process, by allowing it to draw on the knowledge and inventions of others and avoiding investing in the development of these technologies from scratch.[2]

Hence, technology licensing extends the knowledge base of the licensee providing invention benefits through scale. In addition, it broadens the licensee's invention scope by increasing the number of possible recombinations that could produce types of innovation (Ahuja and Lampert 2001; Fleming 2001; Henderson and Cockburn 1994). The licensed technology empowers the licensee by boosting the knowledge creation process leading to the development of inventions. It allows the licensee to savor the benefits of complementarities between the licensee firm's internal knowledge base and the licensed-in technology (Veugelers and Cassiman 1999), which, in turn, allows the firm to invent more broadly and extensively. This argument is in line with the study by Lowe and Taylor (1998), which investigates the role of licensing in the development of new products and processes. They argue that there are complementary benefits deriving from the combination of internal research, development investment, and inward technology licensing, which increase a firm's invention rate. Lowe and Taylor interpret this as the licensee enjoying capability building benefits through its licensing-in activity. In line with this reasoning, we argue that licensing-in fosters learning, which, in turn, increases the number of possible recombinations of the knowledge available to the firm, thereby boosting the licensee's invention rate. We can formulate the following hypotheses:

[2] The markets for technology literature argues that when licensing-in involves patents, it produces stronger positive externalities given the liquidity of this form of codified knowledge (e.g. Arora et al. 2001). Patents promote spill-over effects attributable to technological knowledge circulation (Arrow 1962; Motohashi 2006; Rivera-Batiz and Romer 1991). According to David and Olsen (1992), patents enable the innovation process to be speeded up, based on learning-by-doing and, thereby, boosts the diffusion of existing innovations. Patents also play the role of *hostage* in a contract by making the licensor more willing to purposively provide know-how to the licensee to allow for a better exploitation of the licensed patents and achieve a better outcome, which is in the interests of both parties (Arora 1996). Technology licensing becomes the definitive channel through which this diffusion process occurs.

Hypothesis 1a: Licensees are more likely to introduce inventions.

Hypothesis 1b: Licensees introduce more inventions.

A License-to-Invent in the Licensed Technology

There are invention advantages from licensing-in related to an invention strategy based on the licensed technological class. Integration of the licensed technology and related learning effects may shift the licensee's technological focus, promoting search in the technological class specified in the license agreement. Technology licensing can be considered a shift towards or consolidation of that technology, or an adjustment to the invention effort into that particular technological field. Technology licensing induces changes to, or new search patterns, thereby becoming the means through which licensees develop dynamic capabilities. Dynamic capabilities, defined as "the firm's ability to integrate, build and reconfigure internal and external competences to address rapidly changing environments" (Teece et al. 1997: 516), are major advances in the licensees' invention expertise in the contractually specified technology. As emphasized by Teece (2008), these capabilities encompass the capacity to sense and size up external as well as internal opportunities and threats, and the capacity to reconfigure intangible and tangible assets in an entrepreneurial fashion, which leads to the achievement of sustainable competitive advantage in the business environment. Indeed, Daneels (2002) argues that developing a new product involves not only creating the knowledge contributing to the invention, but also developing competences that contribute to the firm's further renewal. Based on this reasoning, we argue that by engaging in a licensing agreement, the licensee opens up a channel of information from the licensor, which furnishes it with competences that assist in the development of new inventions by the licensee, in the same technological class. Arguably, licensees retrieve competences that lower the bar to them becoming inventive in the technology in question, due to improved understanding and an upgraded ability to build a knowledge base in this field of expertise. A license, therefore, enables the creation of absorptive capacity (e.g. Cohen and Levinthal 1989; Cohen and Levinthal 1990), which, in Zahra and George's (2002) conception, is the capability to acquire, assimilate, transform, and exploit externally sourced knowledge. Licensing in a technology may redirect these capabilities towards the licensed technology, and focus the firm's invention strategy on this particular part of the innovation landscape. Zollo and Winter (2002) develop a theoretical framework in which organizational competencies lie along an evolutionary path defined by distinctive knowledge accumulation processes that occur over time. Technology plays a particular role in this evolution and, according to Teece et al. (1997), conditions the dimensions of the path of organizational capabilities. Thus, licensing-in can be considered to be one of the processes sustaining *dynamic capabilities in action*, since it may open up pathways to reinforced or even new capabilities within a specific technological domain. We argue here, that the license agreement influences this path and assists the licensee to be inventive in the licensed technology, which leads to the following two hypotheses.

Hypothesis 2a: Licensees are more likely to introduce inventions in the technological class specified in the license agreement.

Hypothesis 2b: Licensees introduce more inventions in the technological class specified in the license agreement.

Technological Specialization and Post-Licensing Invention Behavior

While there is good reason to believe that licensing-in promotes firms' invention performance, it also seems clear that particular antecedents shape how licensing promotes or inhibits invention. The differences between technologically specialized and diversified firms have been closely scrutinized (e.g. Santaló and Becerra 2006; Villalonga 2004). Inventive firms are specialized or diversified in patenting activities, depending on whether they concentrate on a few technologies or invent more widely. The firm's specialization may be a by-product of the tendency for the firm's invention practices to be path-dependent in the sense that past invention practices dictate the firm's current and future invention practices and constitute boundaries to what the firm might achieve technologically, currently and in the future, by delineating its technological trajectory.

In the context of this paper, we take this argument further by proposing that firms are not only locked into a particular technological trajectory in terms of the invention space available for opportunity seeking. They also set boundaries to the practices they employ in their invention activities. Our arguments fit within the framework proposed by Miller (1993) and Miller and Chen (1996), They argue that firms suffer from what they call simplicity, defined as the tendency to concentrate intensively on a few central activities. As Miller (1993: p. 117) states, there is "an overwhelming preoccupation with a single goal, strategic activity, department, of worldview – one that increasingly preclude consideration of any other". Thus, firms find it difficult to strive for multiple goals or achievements. Rather than seeing this property of simplicity as common to most organizations, we perceive this pre-occupational behavior to be an idiosyncrasy that is gradually acquired, such that some firms display high levels of simplicity and others do not. In a licensing context, we suggest that licensees displaying high levels of simplicity are very likely to draw on this practice ex post of signing the license agreement. Technological specialization suggests that the firm concentrates intensive invention efforts on a single or few technological classes. Hence, it is an indication of the degree to which the organization is characterized by technological simplicity. Displaying simplicity prior to licensing activity increases the likelihood that a licensee will pursue similar behavior and focus only on a narrowly defined part of the innovation landscape. On the other hand, a technologically more specialized licensee, after entering into a license agreement, will display an invention behavior that is concentrated around the licensed technology . We test the following hypothesis:

Hypothesis 3: Licensees with a high degree of technological specialization invent more narrowly in the licensed technological class.

Technological Familiarity and Post-Licensing Invention Behavior

The extant literature on technology transfer (Arora and Gambadella 1990; Cassiman and Veugelers 2006; Cohen and Levinthal 1989; Gambadella 1992; Granstrand et al. 1992; Lin 2003; Lowe and Taylor 1998; Tsai and Wang 2007) argues that the nature of the acquired technology *per se* is not sufficient to ensure that the recipient firm assimilates and integrates it. The extent to which acquisitions of external technological knowledge foster the process of technological learning depends on the capabilities of recipient firms to absorb this knowledge. Along these lines, Lane and Lubatkin (1998) introduce the concept of firm's *relative absorptive capacity*, referring to the alliance partners' abilities to learn from one another, based on overlaps in their mutual knowledge bases. Mowery, Oxley and Silverman (1998), for instance, find that joint venture partners have significantly higher levels of technological overlap than non-partners, suggesting that such overlap - representing a relative measure of relatedness among knowledge bases - is a significant factor in the partner selection decision.

In the licensing context, the relevant overlap is between the licensed technology and the licensee's knowledge base. The higher the familiarity – "the degree to which knowledge of technology exists within the company, but it is not necessarily embodied in [its] products" (Roberts and Berry 1985: 3) - the lower the learning costs associated with the integration of the licensed technology. This, in turn, facilitates its fruitful exploitation: the transferred technology is more easily mastered by the licensee and can be implemented more quickly (Kim and Vonortas 2006).[3] However, it also sets boundaries to the extent of technological learning. The inventions introduced after licensing-in will be predominantly in the technological class embedded in the license agreement. Based on these arguments we propose the following hypothesis:

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[3] Kim and Vonortas (2006) provide a measure of technological proximity based on the "distance" in the "technological space" between licensee and licensor. They suggest that the degree of similarity in the technological profile of licensor firm *i* and licensee firm *j* in year *t* increases the probability that licensor firm *i* will license its technology to licensee firm *j* in year *t* (Kim and Vonortas 2006: 278). We believe that this proxy is misleading when the licensed technology does not reflect the licensor's core technologies – which is frequently the case. While the physical proximity of the licensed parties may lower the transaction costs related to the licensing negotiation phase, the overlap between the licensee's knowledge base and the licensed technology is more relevant for the post-licensing integration phase.

Hypothesis 4: Licensees familiar with the licensed technology prior to licensing-in, invent more narrowly within the licensed technological class.

METHOD AND DATA

This section describes the data and operationalization of the variables, and the econometric approach adopted to study the hypotheses.

Data

We exploit three data sources. First, a sample of patent licensees drawn from an extensive cross-sectional data set on intellectual property transactions, organized and maintained by the Financial Valuation Group (FVG).[4] Apart from providing information on licensees, the data provide information about licensors, and time and terms of the agreement. The data include a wide range of different types of license agreements such as Technology/Patent, Software, Trademark, Franchise, Copyright, and Product licenses. However, in the present research we are interested in licenses implying the exchange of technology (in the form of patents); this explains our exclusive focus on Technology/Patent license agreements. In some cases, information on the licensed patent(s) was not retrievable either because the original license agreement was unavailable and not summarized in firm filings (e.g. S1, 8K, and 10K) at the Securities and Exchange Commission (SEC) or because the license agreement was subject to a confidentiality agreement. These agreements are excluded from our analysis.

We integrated the license agreement data with US Patent and Trademark Office (USPTO) data drawn from the NBER (National Burea of Economic Research) patent database, which allows us to use patent applications as indicators of invention. The NBER database is consulted for information on invention and innovation as well as technology partnering data. It covers all patents granted by the USPTO up to 2002 and includes a large number of key variables useful for the present study (see Hall, Jaffe and Trajtenberg (2001), for a detailed description of the dataset). As this is a patent level database, it includes information describing characteristics such as International Patent Classification (IPC) classes, date of patent application and grant, number of claims made and number of citations made. However, as already stated, the NBER patent database ends in 2002 and some of the license agreements studied were signed in 2001. Thus, having identified our total sample, we consulted the USPTO patent database search engine to update the NBER dataset to 2008 for our sample firms.

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[4] FVG is one of the leading business valuation consulting and litigation service firms in North America, see http://www.fvginternational.com/index.html, accessed June 2009.

The primary aim of the paper is to investigate the effect of licensing-in on licensees' post-technology acquisition invention performance. For analytical purposes we redefine the question to: "Would licensees find their searches for new inventions less effective had they not signed license agreements?" thus creating a setting that points to particular analytical methods. Firms are never observed as licensees (treated) and non-licensees (non-treated) simultaneously. Our endeavor, therefore, necessitates that we obtain a non-treated sample of non-licensees. It is a clear requirement that a control sample useful for comparison, should consist of firms that are similar to the group of licensees in the sense of being equally likely to have signed similar license agreements, but chose not to do so.

We relied on a combination of exact and propensity score matching to generate the sample of non-licensees. The exact matching procedure ensures that particular characteristics of the licensees are duplicated exactly in the control sample. In our case, we ensured, first, that the snapshots of licensee and non-licensee were at exactly the same point in time, that is, in the same month as the license agreement was signed. Second, we checked that licensee and matched non-licensee invent primarily in the same technological class, thus ensuring that they will likely compete in the same technology.

The propensity score matching procedure is based on matching estimated likelihood given observables rather than regressors (Rosenbaum and Rubin 1983). This procedure ensures that licensees and the non-licensees are equally likely to have signed license agreements given some specified co-variates. One of the advantages of the propensity score matching procedure is that it allows the use of multiple continuous regressors to identify a matched control sample. In this paper, we rely on a logistic regression method to obtain the conditional probability of becoming a licensee given the firm's specific characteristics. We also matched with replacements allowing for a non-licensee to be matched multiple times, for several licensees.

Heckman, Ichimura and Todd (1997) underline that propensity score matching and its ability to find appropriate matched firms, relies heavily on the data and measures used being appropriate to obtain useful probabilities of being treated (in this case, of being a licensee). Optimal results from the matching procedure are obtained when definitions and data measures are the same across treated observations and the control group. The choice of input variables is also important in the estimation of propensity scores. In this paper, we consider technology licensing to be an integral part of the firm's invention and patenting strategy. We therefore need matching variables that convey information on these particular dimensions. In addition, the objective is to study the impact of licensing on the firm's technological advancement. Thus, for the matching procedure we chose variables suggestive of the firm's technological capability and invention strategy. This ensures, first, that we are comparing firms likely to perform equally well in terms of our dependent variable.

Second, it ensures that our use of invention strategy variables in creating the matched sample has reduced the probability that a significant licensing variable will be attributable to endogeneity triggered by differences in the approach to technological advances that otherwise might be expressed by the license agreement variable.

We extracted 20 possible non-licensee matches for each licensee using the propensity score matching procedure. Using the Thomson Research Database, we manually checked every firm for indications of technology licensing or patenting over a five year period[5] from the time of the signing of the license agreement by the licensee firms. S1, 10K, and 8K filings often reveal whether a firm has engaged in licensing activities. Following this procedure, in cases where these checks revealed no evidence of licensing activity, we searched on Google using “License agreement” and company names, as search criteria. Google searches SEC filings for licensing activities. In the case that a licensee has not reported its licensing activities, Google search may identify them via the licensor’s filings. We categorized firms as non-licensees if none of these sources revealed any evidence of the contrary. We limited our search to one non-licensee per licensee, but ensured that the match survived for at least five years after the year of the signing of the license agreement. Most non-licensees are still in business at present. This may create some bias in the sense that licensees may not exhibit the same persistence in terms of survival. However, as such bias would go against our hypotheses, we consider that it adds strength to any supportive findings.

We exploited the NBER patent data to create the matching variables. Accordingly, we exclude non-licensees that did not patent with the USPTO prior to signing the license agreement. Firms that have never patented with the USPTO may not have invention strategies and, therefore, may have engaged in licensing for other reasons. In addition, non-patenting firms may rely on alternative appropriability strategies which prevent them from patenting, or from patenting through the USPTO. Including them in the sample might introduce bias in the estimations. Since we do not impose the same requirement for licensees, this could cause bias that would work against our hypotheses making any supportive results conservative.

We excluded a small number of licensees because we were unable to find fitting matched non-licensees. For example, it is almost impossible to find comparable non-licensees for companies such as Microsoft, Abbott Laboratories, Siemens, IBM, Procter and

[5] The choice of 5 years was deliberate and is consistent with previous work on patents (e.g. Lanjouw and Schankerman 1999; Sampat et al. 2003), which analyzes patent quality based on number of forward citations a patent receives within 5 years of its application date. This is tantamount to saying that previous patenting activity is deemed to exhibit an effect on current outcomes (the license decision) for at least 5 years. Symmetrically, the decision to license a particular patent can be used to guide future decisions within a time frame of 5 years. We are cognizant of possible precision grinding errors. For this reason, we also conducted analyses using different time horizons (4 vs. 6 years): the results did not differ significantly.

Gamble, Ericsson, and Hitachi, due to the immense size of their patent portfolios. Our final sample is 133 licensees and 133 non-licensees.

Dependent Variables

One of the aims of the paper is to understand how signing a license agreement helps to boost the invention performance of the licensee - first, in terms of invention generally, and second, vis-a-vis invention in the specific licensed technology. We measure these two types of invention performance by counting the number of patent applications within five years of the reference license agreement, and the number of patent applications in the same IPC code(s) of the licensed patent(s) within five years of the license agreement. By using the date of application rather than date of granting of the patent, we lower the probability that an invention was generated before the license agreement. However, since the updated NBER patent database contains only successful patent applications, our definition of invention is grantes USPTO patents.

By dividing the number of patents in the technological classes contained in the license agreement by the general invention measure, we obtain a measure of how narrowly the firm invents in the licensed technology. This measure acts as the dependent variable in our investigation of hypotheses 3 and 4. We disregard firms that did not patent at all within the 5 years.[6]

Our sample contains license agreements signed in 2001. Investigating inventiveness for the five years after the license agreement means we count patent applications up to 2006. However, because we updated the NBER data to May 2008, applications filed before 2006, but not granted by May 2008 may cause some underestimation of observations in later license agreement years. However, we do not expect this to cause serious bias in our estimates as we have no reasons to suspect that the patent office treats applications from the licensees and non-licensees differently.

Explanatory Variables

The matching procedure provides a dummy variable for studying the effect of signing a license agreement or not, resulting in a grouping of two equally represented observations of licensees and non-licensees. The benchmark is the non-licensees, leaving the estimate as a measure of the effect of having chosen to sign a licensee agreement.

Hypothesis 3 suggests that firms familiar with the licensed technologies are more likely to concentrate their post-licensing patenting in the technological class of the contractual

[6] We considered the possibility that leaving out licensees that did not patent subsequent to the license agreement would cause selection bias. Following the approach developed in Heckman (1979), we used the Inverse Mills Ratio as an added explanatory variable and found no indication that our results suffer from selection bias.

agreement. As an indicator of technological familiarity with the licensed technology, we employ Ziedonis's (2007) *focus* index. This is a measure of the share of patents granted in the six years prior to licensing, that are in the same IPC as the patents included in the license agreement of reference.

We use the Herfindahl index to calculate the technological specialization of the firm prior to the license agreement using the IPC codes of the firms' patent portfolio. This is based on the share of patents across technological classes. The lower the index, the less technologically specialized the firm and, hence, the lower the level of simplicity of the invention behavior.

Matching Variables

The use of matching variables has two objectives. First, it ensures that licensees and non-licensees are equally likely to have signed the license agreement in question. Second, it describes the technological capability, learning potential, invention strategy, and inventiveness of the firms, thereby ensuring that we are investigating comparable subjects. In this paper, we use five variables. First, a measure for how extensively a firm has invented prior to licensing-in, based on patent stock. This is measured by the logarithm of the firm's number of patents. Organizations with a larger pool of potential complementary technological assets are more likely to license-in since they have a greater chance of successfully combining the acquired technology with in-house technology. In addition, based on its previous extensive invention performance, it is likely that the firm will invent in the future, as a result of path dependence in invention activities.

Second, firms that have demonstrated an ability to introduce major inventions, reflected in the number of citations their inventions receive, are more likely to continue to pursue an invention strategy. In addition, numerous citations may also be an indicator of extensive network relations, which, in turn, may increase the potential for licensing activity. Thus, we use the average number of citations to the firm's patents as a matching variable.

Third, patenting frequency is quantified as the average time between patents granted prior to the license agreement. This is calculated as the number of years between the license agreement and the first patent granted, divided by the number of patents granted. Higher frequency is expected to increase the likelihood that the firm will patent again, and will patent more extensively. It also indicates the intensity of the firm's invention strategy, pointing to external search behavior.

Fourth, technological diversity is measured as the number of different IPC codes the firm has patented in prior to the license agreement. Firms exhibiting high technological breadth are considered more likely to patent in general, compared to inventing narrowly in the technological class specified in the license agreement. In addition, a high level of diversity suggest that the firm has rather extensive invention capabilities, which, in turn, may increase the number of potential licensing-in technologies.

The fifth variable is based on firms' co-patenting activities indicating openness to cross-organizational collaboration. cross-organizational collaboration may enhance an organization's inventiveness and be indicative of the likelihood of the firm engaging in licensing activity. We use a prior to license agreement co-patenting dummy as measure of this.

Control Variables

We account for the firm's search strategy, using the Katila and Ahuja (2002) search scope and search depth measures, which hark back to March's (1991) exploration-exploitation dichotomy. Search depth is defined as the average number of times a firm cites patents repeatedly in its patent applications. Search scope is defined as the proportion of citations in a firm's patent applications for a particular year, that were not cited in the previous five years.

The NBER dataset reports a generality index for each patent. This is based on the share of citations a patent receives from different technological classes. Summing up the squared shares produces a measure suggesting the degree to which the technology is applicable in multiple technological contexts (see Hall and Trajtenberg 2004 for details). We use the maximum generality index of the firm's patents prior to the reference license agreement, as a control for the firm's ability to produce inventions useful as inputs to multiple technological classes. Following Lanjouw and Schankerman (1999), firms' technological complexity is measured by the average number of claims on patent grants prior to the license agreement. Familiar with complex technologies promotes the ability to absorb new knowledge and integrate it into their existing knowledge bases (Lin 2003).

We use the NBER technological classifications as a control for differences in patenting activities across technologies. We use a categorical distinction to control for the size of the firm. The categories are: Small firms defined as less than 100 employees; Medium firms defined as 100-1,000 employees; and Large firms defined as firms with over 1,000 employees. Finally, we control for geographical location by a dummy for whether the firm is North American or not. The assumption is that Japanese and European firms may exhibit lower propensities to patent at the USPTO compared to North American firms since their first choice may be their local patent office.

Method

The first four hypotheses (1a, 1b, 2a, and 2b) categorize invention performance as: 1) whether a firm produces any inventions at all; and 2) how many inventions a firm produces.

We follow Pohlmeier and Ulrich (1995) and apply a hurdle/two-part model to investigate a two-stage process. In this paper, the first stage relates to the ability of the firm to become an inventor – to overcome the barriers to invention. The second stage involves how extensively the firm is able to invent. Adopting this approach, we investigate first what drives the likelihood of producing any inventions at all, and second, once a firm exhibits patenting activity, what drives the number of inventions a firm produces.

The hurdle model involves two density estimations. The first estimation explains the observations of a positive number of inventions determined by a density, $f_1(.)$, so that $Pr[y>0]=f_1(y)$. The second is a truncated density function estimation explaining the number of inventions, disregarding zero observations. This may be written as $f_2(y|y>0)=f_2(y)/(1-f_2(0))$. The hurdle model multiplies $f_2(y|y>0)$ with $(1-f_1(0))$ to ensure that the probabilities of the outcomes sum to unity. The hurdle model is reduced to the standard count model in cases where $f_1(.)=f_2(.)$. We follow McDowell (2003) and use a complementary log-logistic specification for the first part and a truncated Poisson specification to model the positive outcomes in the second part. In the two regression specifications we employ the same variables as regressors. The Huber-White sandwich estimation technique is used to correct standard errors for possible heteroskedasticity.

To test hypotheses 3 and 4, we develop a model specification that explores the type of licensee, which, subsequent to the license agreement, tends to invent narrowly in the licensed technologies. This is done by examining only the inventive licensees and regressing the explanatory variables used in the previous regressions against the number of inventions in the licensed technologies relative to the total number of inventions introduced by these licensees. This measure is truncated at zero for those observations that did not invent in the licensed technologies, and at 1 for those subjects that only invent in the licensed technologies. We use the two-limit Tobit regression specification to model this, as prescribed by Tobin (1958).

RESULTS

Descriptive Statistics

The Descriptive statistics and correlations between variables are presented in Table 1 reveal that the analysis is unlikely to suffer from multicollinearity. This is confirmed by a variance inflation factor analysis. Table 1 shows that approximately 59% of firms engaged in some patenting activity within the five years following the license agreement, and about 24% of firms patented in the IPC codes of the patents included in the reference license agreement.

INSERT TABLE 1 ABOUT HERE

Table 2 presents the distribution of observations across the three categorical variables included in our model. The sample is split between licensees and non-licensees. In terms of firm size, Table 2 shows that the sample contains a majority of small firms. However, taking the skewness of the population size distribution into consideration, it is evident that licensing-in is more likely to be a large firm strategy. Although the size variable is not used in the matching procedure, there is an overwhelming similarity between the licensee and non-licensee samples in terms of firm size distribution. Table 2 also shows that there are geographical differences between licensees and non-licensees. In our sample the relative number of firms categorized as Non-North American is higher for non-licensees. This may be a by-product of licensing being more widely used as an integrated activity in the invention strategies of North American firms, making it more difficult to find a North-American match that is also a non-licensee. This is also consistent with evidence on the markets for technology which suggests that American firms lead in terms of technology exchange, compared to the rest of the world (e.g. OECD 2007).[7] Also, and not surprisingly, we observe an equal number of licensees and non-licensees in the six different technological classes attributable to the technological class used in the exact matching procedure. However, we can also see that a substantial number of observations patent primarily in the “Drugs and Medical” and the “Chemicals” technological classes.

INSERT TABLE 2 ABOUT HERE

The propensity score matching procedure matches not on regressors, but on estimated likelihoods given regressors. We cannot be certain, therefore, that the matching variables are distributed equally across the licensee and non-licensee samples. We ran a probit regression using the licensee dummy as a dependent variable, and propensity score matching variables and the technological class dummies used in the exact matching procedure as explanatory variables. We found no significance, and a pseudo R-square only marginally above 0. Also, the Chi-square statistic suggests a 98% likelihood of all parameter estimates to be equal to zero, indicating that the matching procedure was successful in finding matching firms based on these input variables. These results also suggest that any significance found in the hurdle models with respect to the matching variables can be attributed to within-group correlations rather than between-group differences.

Licensing and the Invention Performance of the Licensee

The results from the two hurdle models are reported in Table 3. The columns to the left refer to the regression for inventions in general, where the dependent variable is a

[7] According to the 2007 OECD Science, Technology and Industry Outlook (OECD 2007: 12) “Royalty receipts from outward licensing have been estimated at 6.0%, 5.7% and 3.1% of total R&D spending for US, Japanese and European firms, respectively, suggesting that technology licensing markets are better developed in the United States than elsewhere”.

dummy for whether the firm introduced any inventions at all (complementary log-logistic regression) and the total number of patents after the firm invented at least one (truncated Poisson). The columns on the right show the regression results for inventions in the licensed technology with a similar set-up, based on inventions in the same technological class as that of the licensed technology.

INSERT TABLE 3 ABOUT HERE

Hypotheses 1a and 1b are strongly endorsed by the results. The licensee variable is highly significant in explaining both the likelihood of inventing and the number of inventions introduced after the signing of the reference license agreement. Our analysis also provides support for hypothesis 2a, by suggesting that licensing-in is affiliated to a higher chance of introducing new inventions in the licensed technology. We find no support for hypothesis 2b. Once non-licensees have overcome the hurdle of inventing in the technology acquired by the licensees, they seem to be equally well equipped to invent extensively in this particular technology.

These regressions provide evidence that licensing agreements allow licensees to enjoy spill-over effects from the licensed technology and the licensor in the form of knowledge flow and learning, facilitating patenting in the licensed technology as we as in other technology classes than those specified in the license agreement.

Among the other results presented in Table 3, we highlight the following as being integral to our analysis. We find that search depth and search scope increase the firm's likelihood of introducing new inventions in general, but that search scope, at best, has only a weak effect on raising the probability of inventing in the licensed technology. However, the results do suggest that firms employing a search depth strategy are hampered in terms of the number of inventions filed in the licensed technological class, while firms employing a search scope strategy engage in greater invention activity in general, and are more active in invention in the technology specified in the license agreement. Technological specialization seems to increase the likelihood of inventing generally, as well as becoming successful in producing at least one invention in the IPC codes covered in the reference license agreement. The firm's patent stock prior to the license agreement increases the extent of invention regardless of whether it is invention generally or invention in the licensed technology. Furthermore, the regression results suggest that technological experience hampers the extent of invention in general.

Specialization, Familiarity and Narrow Invention Strategy

Table 4 presents the results of the Two-Limit Tobit regression investigating whether particular types of licensees tend to invent relatively more often in the IPC codes of the licensed technology. Table 4 reveals that 98 of the 133 licensees did invent in the five years after the license agreement. It also shows that 38 of the licensees did not invent in the licensed technology at all, and that 13 licensees invented only in that technological class.

INSERT TABLE 4 ABOUT HERE

Hypotheses 3 and 4 suggest that technologically specialized licensees, and licensees familiar with the licensed technologies, tend to be more likely to exploit the narrowly specified technologies covered in the license agreement and to search the invention landscape in the area of the licensed technologies. We provide support for both these hypotheses in finding significant positive estimates for both specialization and familiarity.

The coefficients of our two dummies for technological classes – namely the “Drugs and Medical” and the “Electric and Electronics” – are also significant. This suggests that inventions in these technology classes are relatively less used for general technological advancement than technologies licensed in the chemical technology class (benchmark category).

DISCUSSION

This paper was motivated in part by the recent trends in firms’ approaches to increase their invention rate. Firms are adopting more open models of innovation, thereby taking advantage of the opportunities that the markets for technology may present, to foster and unlock the potential of firms’ internal R&D efforts. In particular, firms are embracing inward technology licensing as a means to realize their invention objectives. Indeed, licensing has become one of the most visible mechanisms of knowledge transfer among firms and one of the more accessible means of tapping into the knowledge bases of other firms.

Licensing-in strategies are traditionally considered to be driven by the licensee’s desire to get rapid access to proven/mature technology. However, such practices are increasingly being recognized as strategic and for the pursuit of other goals, such as technological learning, which, in turn, leads to the development of new technological capabilities. To the best of our knowledge, very few studies have attempted to address whether and to what extent licensing-in generates new technological advances. This is despite the increasing empirical evidence that licensees gain competitive advantage, and even achieve technological leadership, by leveraging and exploiting the learning opportunities that licensing practices enable.

This paper fills a gap in the existing knowledge by providing strong quantitative evidence of licensing functioning as a catalyst for developing and introducing new inventions. The results suggest not only that licensing increases the likelihood of introducing new inventions, but also that it increases the number of inventions that the licensee is able to introduce. Thus, licensing promotes invention activities in general, enabling the firm to enter technology fields beyond those included in the license agreement. However, we have also shown that licensing increases the likelihood of introducing a new patent in the technological class embedded in the license agreement.

In addition, our results suggest that there are particular antecedents that drive the licensee to focus on the technological class specified in the license agreement. Technological specialization and familiarity with the licensed technology promote focused invention activities. Licensees with high levels of specialization and/or technology familiarity tend to invent primarily in the regions of the technological landscape of the licensed technology. Accordingly, diversified firms and licensees relatively unfamiliar with the licensed technologies tend to explore the invention landscape more widely than the license agreement technology focus. This indicates that there is a need to focus on learning patterns and their related invention and innovation effects when deciding about licensing-in. This observation is highly relevant to a better understanding of the path dimensions of dynamic capabilities (see e.g. Teece et al. 1997), an aspect that has received far less attention than, for example, resource constellations, and the managerial and organizational processes involved in changes to the firm's resource base over time. Our empirical observations indicate that licensing-in not only is a means for deepening already existing knowledge sets, but also induce new search patterns, which ultimately may lead to a broadening of the firm's patenting activities and new combinations of existing and new knowledge. Hence, technology licensing could reduce the path dependency of established firms and trigger the pursuit of new invention endeavors. This is in line with the suggestions in Granstrand (1998), which stress that technological opportunities can be created through the combination and cross-fertilization of old and new technologies, and that combinatorial possibilities grow exponentially when new technologies are added to the firm's existing technological base. Thus, the introduction of new technologies via licensing-in constitutes a potentially important vehicle for generating new opportunities for invention by inducing new search patterns and technology combinations. This may lead to a widening of the technological trajectory that influences the firm's strategic maneuvering space. The different search patterns triggered by different licensing approaches can also be important for understanding the flexibility of a firm's resource base, an aspect seen as important for firms to remain competitive over time (see e.g. Wernerfelt (1984) and Sanchez (1995)). Thus the inherent flexibility of a resource base, which, in technology-based businesses, can play a significant role in challenging relentlessly dynamic and entrepreneurial markets, may be affected by licensing-in activities. These activities may enable firms to open up the box of learning opportunities for diverse or more consistent uses of their knowledge bases.

Limitations

This paper suffers from a number of limitations. Technology licensing-in does not necessarily need to be an integrated part of a invention strategy, but may be pursued for other reasons. Among other motives, firms may license a given technology as a part of a broader R&D partnership or cross-licensing agreement, or simply because they are forced to do so as they have previously infringed a licensor's property rights (settlement agreement). We are aware of these motives, but since we are concerned in this paper only with technology exchange agreements - which imply a one-way technology/intellectual property rights transfer, from licensor to licensee - we included only those transactions that were originally filed by the parties as (pure) licensing or assignment agreements. Thus, we excluded all other transactions that refer to R&D collaboration, cross-licensing, settlement agreements, and also technology purchases and merger plans[8] that were incorrectly listed under the heading "Transaction/Patent Licenses" in the original dataset. Nevertheless, we are not able to separate agreements that were signed as a way to *pre-empt* a violation of a licensor's intellectual property rights, from those that are an integral part of a licensee's invention activity. Given this, the positive correlation between licensing-in and invention performance may need to be re-evaluated as it points to an unobserved omitted variable that may influence invention performance and promote the decision to license a given technology. However, we consider this case to be unlikely in context of our dataset. We believe that firms engaging in license agreements with the sole purpose of avoiding legal litigation would previously have developed the technology they considered to be in danger of violating the intellectual property rights of the licensor. Hence, we would expect the licensee, in this case, to apply for a patent immediately after signing the license agreement. We studied the time it took for a licensee to apply for a new patent after having licensed the technology and found it to be on average 109 months after signing the license agreement. This long time period suggests that at least the majority of our licensees do not license as a way to avoid legal litigation.

The invention performance of the firm is a time-dependent issue. The cross-sectional nature of our sample limits the scope of the analysis. It may exclude some relevant insights on the dynamics of the licensing-in decision and internal R&D efforts over time. We look only at the effects of a specific decision to license-in on the future inventive outcome of the firm. However, decisions should be framed within the overall strategy of the firm, which is developed and modified across the years. Thus, our analysis is limited in the sense that we assume that the invention strategy of the firm is fixed across time. However, our licensees'

[8] Original documents downloaded from the SEC website generally indicate type of transaction –license, settlement agreement, or the like – in headings. We were careful to check for any information suggesting that the contract referred to another type of agreement than a technology/patent license.

and non-licensees' approaches to technological change may diverge at the point of licensing beyond signing a license agreement. We have no immediate way of controlling for this potential source of bias in the analysis.

The sample of license agreements under investigation all provide information on the technology embedded in the publicly available contract. However, in some circumstances, secrecy may be of major importance to the licensee. Revealing the contents of license agreement may signal the technological strategy of the licensee, thereby providing competitors with information that may be disadvantageous in the invention race. Disregarding license agreements whose contents are not disclosed may lead to a bias in our estimates. However, we contend that this potential bias would go against our primary hypotheses. Consequently, our results should be considered conservative estimates of the relationship between invention performance and taking the decision to license-in a technology.

In addition, it is possible that our matching procedure suffers from unobserved heterogeneity and hence may produce bias due to omitted variables. Our results rest on the specification of the matching procedure. The propensity score-matching procedure has been criticized for bias based on the number of variables used in the matching procedure. We did find some indications that our licensees and non-licensees matched on other dimensions when we considered the control and explanatory variables suggesting the matching process to be robust.

Future Research,

The results of this study indicate clearly that licensing puts the licensee in a favorable position compared to a matched non-licensee, in terms of ex-post licensing inventive performance. The license agreement provides potential learning which extends beyond the specifications in the agreement, for instance, a patent application, and which drives the inventive performance of the licensee. We hypothesize that signing a license agreement also opens up other channels for information flow between licensee and licensor, creating a mutually beneficial collaborative scenario. According to the literature, this applies mostly to patent licensing for a very obvious reason. As patents encompass knowledge that is formally codified and legally enforced, they make licensors more likely to provide the more tacit part of technological knowledge (know-how) which is relevant to understanding and fruitful exploitation of the licensed technology. Follow-up research might investigate whether these channels also help firms to introduce inventions more quickly by accelerating the speed at which they can progress in the innovation landscape, identify opportunities, and overcome innovation barriers. Future work might also look more deeply at the dynamics of cross-organizational collaboration induced by licensing and whether it contributes extensively to our understanding of the role played by formal agreements compared to informal channels of information and knowledge flow. By disentangling the relative importance of these two, we would achieve a scholarly grasp of the true relationship between signing a license agreement and invention performance. We would then understand better whether license agreements are direct drivers of technological change or have an indirect effect driven by the formation of informal network ties that promote knowledge sharing and thereby increase the number of potential new combinations of existing knowledge bodies.

Our study has also investigated the antecedents to a firm's engaging in a licensing agreement in terms of benefiting from the technology it licenses-in. However, given that formal and informal linkages in the formation of channels of information and knowledge between licensee and licensor are extremely important, we propose that future research should investigate the nature of the relationship between licensee and licensor. This is important in two dimensions. First, the overlap between competences and capabilities of licensees and licensors defines the scope of potential knowledge combinations and resulting invention opportunities. Second, following the arguments of Li, Eden, Hitt and Ireland (2008), partner selection is of great importance in the formation of R&D alliances. Trust between partners, and protection of intellectual property rights play a major role in defining the boundaries of the information flow between the parties involved. Similarly, the knowledge and information flows between licensee and licensor may suffer in the presence of mistrust, and restrict inventiveness based on the license agreement. A related stream of research could focus on improving our understanding of the role of certain contractual clauses in the partner selection.

Finally, we propose that future work should investigate whether firms experienced in cross-organizational collaboration are also better equipped to draw advantages from licensing activities. Experience may help firms to select the best partners and also develop their abilities to manage partnerships, maximizing the benefits in terms of knowledge and information flows. Indeed, the facility to define the boundaries of a collaborative partnership is an acquired capability that involves defining the intellectual property rights of traded and produced technological assets as well as setting the scope of the license agreement in terms of knowledge sharing. The right settings may facilitate a more relaxed and more fruitful contractual partnership by promoting trust and mutual understanding. Repeated technology licensing partnerships, for instance, may provide suggestions about the aspects that facilitate and promote a mutually beneficial contractual relationship, leading to a deeper understanding of the dynamics of technology licensing.

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TABLE 1

Means, Standard Deviations, and Correlations[a]

	Variable	Mean	s.d.	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.
1.	Patent Activity	0.59	0.49																				
2.	Nunmber of Patents	10.65	52.77	0.17																			
3.	Patent Activity in Licensed technology	0.24	0.43	0.47	0.27																		
4.	Number of Patents in Licensed Technology	2.92	16.70	0.15	0.85	0.31																	
5.	Share of Patents in licensed Technology[b]	0.22	0.35	.	0.04	0.78	0.21																
6.	Licensee	0.50	0.50	0.30	0.17	0.49	0.17	0.42															
7.	Familiarity	0.16	0.31	0.05	-0.01	0.30	0.07	0.49	0.12														
8.	Technological Specialization	0.54	0.39	0.07	-0.11	0.08	-0.05	0.31	-0.29	0.16													
9.	Patent Stock	1.20	1.12	0.17	0.54	0.19	0.39	-0.10	0.07	-0.10	-0.34												
10.	Average Number of Cites	9.69	14.96	0.09	0.05	0.01	0.02	-0.06	0.01	0.07	0.11	0.11											
11.	Average Time Between Patents	21.58	34.04	-0.15	-0.09	-0.23	-0.09	-0.17	-0.01	-0.08	-0.03	-0.10	0.08										
12.	Technological Diversity	3.05	15.00	0.09	0.74	0.14	0.40	-0.04	0.08	-0.06	-0.14	0.65	-0.02	-0.07									
13.	Technological Collaborator	0.06	0.25	0.06	0.37	0.03	0.31	-0.09	0.11	0.04	-0.09	0.33	-0.01	0.03	0.33								
14.	Search Depth	0.42	1.46	0.19	0.14	0.29	0.09	0.15	0.18	0.12	0.08	0.20	0.04	-0.06	0.13	0.11							
15.	Search Scope	0.32	0.42	0.24	0.14	0.20	0.13	0.02	0.02	0.05	0.03	0.15	-0.03	-0.21	0.06	0.05	0.24						
16.	Technological Experience	59.06	75.71	0.09	0.21	0.04	0.12	-0.11	0.17	-0.16	-0.34	0.70	0.06	0.42	0.39	0.25	0.04	0.02					
17.	Patent Stock Generality	0.55	0.39	-0.04	0.12	-0.04	0.07	-0.16	-0.11	-0.06	-0.20	0.57	0.31	0.02	0.18	0.12	0.13	0.02	0.39				
18.	Average Number of Claims	0.80	2.43	-0.07	-0.04	-0.02	-0.04	0.03	-0.11	0.18	0.21	-0.09	0.34	-0.12	-0.04	-0.07	-0.04	0.17	-0.19	0.07			
19.	Medium Sized Firm	0.28	0.45	0.06	-0.01	0.10	-0.01	0.03	0.07	-0.04	-0.06	0.10	0.08	0.01	-0.02	0.04	0.10	0.12	0.07	0.06	0.04		
20.	Large Sized Firm	0.16	0.37	0.15	0.24	-0.05	0.18	-0.20	-0.04	-0.11	-0.09	0.26	-0.04	0.09	0.23	0.10	-0.00	0.15	0.27	0.05	-0.00	-0.27	
21.	North American Firm	0.86	0.35	0.07	0.06	0.15	0.07	0.20	0.24	0.03	-0.10	0.01	0.12	0.02	-0.01	-0.24	0.07	-0.04	-0.00	0.03	0.05	-0.01	-0.09

[a] The data have 266 observation. Coefficients greater in magnitude than 0.12 are significant at the 0.05 level

[b] Numbers associated with this variable are only based on 149 observations

TABLE 2

Firm Size, Country of Residence and Primary Technological Class of Non-licensees and Licensees

Variable	Licensees	Non-Licensee	Total
Firm Size			
Small	73	77	150
Medium	41	33	74
Large	19	23	42
Geography			
North American	103	125	228
Not north American	30	8	38
Primary Technological Class			
Chemicals	34	34	68
Computers and Communications	13	13	26
Drugs and Medical	48	48	96
Electrical and Eletronics	12	12	24
Mechanical	6	6	12
Others	20	20	40
Total	133	133	266

TABLE 3

Determinants of general and targeted invention performance, results of hurdle models[a]

	General Invention Regression				Invention in Licensed Technology Regression			
	Complementary Log-logistic		Truncated Poisson		Complementary Log-logistic		Truncated Poisson	
Explanatory Varibales								
Licensee	1.408 ***	[0.252]	1.136 ***	[0.282]	3.625 ***	[0.865]	-0.329	[0.641]
Familiarity	0.194	[0.323]	-0.124	[0.446]	2.174 ***	[0.459]	-0.462	[0.672]
Technological Specialization	1.632 ***	[0.329]	-0.441	[0.379]	2.000 ***	[0.564]	1.670 **	[0.792]
Matching Variables								
Patent Stock	0.517 **	[0.254]	0.610 ***	[0.145]	0.818 **	[0.324]	0.710 **	[0.298]
Average Number of Cites	0.022 ***	[0.008]	0.011 *	[0.006]	0.001	[0.011]	-0.010	[0.010]
Average Time Between Patents	-0.011 **	[0.004]	-0.004	[0.008]	-0.021 *	[0.011]	-0.023	[0.019]
Technological Diversity	-0.029 ***	[0.008]	0.002	[0.004]	-0.005	[0.009]	-0.010	[0.007]
Technological Collaborator	0.106	[0.526]	0.293	[0.334]	-1.629 **	[0.719]	2.235 ***	[0.651]
Control Variables								
Search Depth	0.694 ***	[0.256]	-0.094	[0.064]	0.111	[0.128]	-0.246 ***	[0.088]
Search Scope	0.518 **	[0.245]	0.942 ***	[0.223]	0.661 *	[0.391]	1.747 ***	[0.514]
Technological Experience	0.002	[0.003]	-0.006 ***	[0.002]	-0.003	[0.004]	0.000	[0.003]
Patent Stock Generality	-0.515	[0.355]	-0.513	[0.318]	-0.962	[0.634]	-1.857 **	[0.775]
Average Number of Claims	-0.151 ***	[0.053]	-0.040	[0.061]	-0.046	[0.069]	0.115	[0.094]
Firm Size								
Large	0.855 ***	[0.295]	0.909 ***	[0.305]	-0.133	[0.525]	-0.030	[0.779]
Medium	0.205	[0.240]	0.680 **	[0.288]	0.332	[0.350]	0.494	[0.604]
Small	Benchmark		Benchmark		Benchmark		Benchmark	
North American Firm	0.194	[0.327]	0.693	[0.630]	0.418	[0.929]	12.649	.[b]
Primary Technology Dummies								
Computers and Communications	-0.097	[0.349]	0.107	[0.509]	-0.691	[0.664]	-0.115	[1.342]
Drugs and Medical	0.114	[0.268]	0.207	[0.281]	0.218	[0.414]	0.452	[0.843]
Electrical and Eletronics	0.052	[0.436]	0.344	[0.279]	0.628	[0.623]	0.189	[0.643]
Mechanical	0.628	[0.514]	-0.064	[0.525]	0.749	[0.816]	-0.637	[0.847]
Others	0.072	[0.331]	-0.013	[0.398]	1.208 **	[0.574]	-0.209	[0.809]
Chemicals	Benchmark		Benchmark		Benchmark		Benchmark	
Constant	-2.584 ***	[0.527]	-0.197	[0.632]	-6.470 ***	[1.145]	-12.459 ***	[0.963]
Number of Observations	266		157		266		64	
Log-Likelihood	129.074		-950.969		-68.060		-325.627	
Wald Chi-Square	76.452 ***		7995.502 ***		84.804 ***		1560.044 ***	
Pseudo R-Square			0.808				0.705	

*: p<.1, **: p<.05, ***: p<.01

[b]Very few non-North American Firms patents in the IPC codes of the license agreement of reference. Consequently the table exhibits a mising standard deviation for this variable and inflates its estmiate and the intercept. Leaving it out reveals that none of the other estimates are influenced by this.

TABLE 4

Two Limit Tobit Models of Share of Inventions in Licensed Technology

	Share of Inventions in Licensed Technology Regression		
Explanatory Varibales			
Familiarity	0.769	***	[0.208]
Technological Specialization	1.024	***	[0.278]
Matching Variables			
Patent Stock	0.065		[0.131]
Average Number of Cites	-0.003		[0.005]
Average Time Between Patents	-0.006	*	[0.003]
Technological Diversity	0.003		[0.003]
Technological Collaborator	-0.401	**	[0.193]
Control Variables			
Search Depth	-0.045	*	[0.024]
Search Scope	0.152		[0.128]
Technological Experience	-0.000		[0.001]
Patent Stock Generality	-0.067		[0.248]
Average Number of Claims	0.005		[0.035]
Firm Size			
Large	-0.090		[0.200]
Medium	0.119		[0.131]
Small	Benchmark		
North American Firm	-0.131		[0.202]
Primary Technology Dummies			
Computers and Communications	-0.328		[0.256]
Drugs and Medical	0.306	**	[0.148]
Electrical and Eletronics	0.434	**	[0.202]
Mechanical	0.263		[0.247]
Others	0.204		[0.203]
Chemicals	Benchmark		
Constant	-0.528	**	[0.245]
Sigma Constant	0.414	***	[0.046]
Number of Observations	98		
Number of Left Truncated Observations	38		
Number of Right Truncated Observations	13		
Log Likelihood	-56.626		
F-Statistics	4.646	***	
Pseudo R-Square	0.404		

Note: *: p<.1, **: p<.05, ***: p<.01