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An Analysis of Pure-Revenue Licensing

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ABSTRACT

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An Analysis of Pure-Revenue Technology Licensing[*]

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Abstract

This paper analyzes pure-revenue technology licensing, where licensors solely seek obtaining royalties. Since strategic concerns are left aside, the licensing decision is mainly driven by the features of the innovations. Our aim is to identify such characteristics. We use the NBER Patent Citations Database to explore different dimensions of the patented technologies present in *yet2.com*, a marketplace likely to capture pure-revenue transactions. Our findings point out that these technologies differ from the mean technology of the licensor's portfolio with respect to importance, innovativeness, scope, complementarity and fit into the firm's core. Results increase our awareness on the drivers of technology licensing decisions.

1. INTRODUCTION

When a firm comes up with a new technology, being it a new process or product, she will try to prevent its leakage to competitors in order to be able to enjoy a monopoly position. This protection is achieved by different means (Cohen et. al, 2000): secrecy and intellectual property protection are the two extremes of a continuum of options. If such protection is effective, she will indeed exploit the monopoly position either by herself or through another party. The latter case occurs when she has no capabilities or abilities to exploit the technology efficiently and she either sells the technology or the rights to use it, i.e. she licenses.

Licensing is the way of life of some science-based firms, which sell in the market for technology instead of the market for final products. As well, firms that have development capabilities, may license out as an alternative to in-house development or a by-product of it. In the latter case, licensing and own development may take place in the same or a distinct geographical or product market. Licensing in the same market implies the introduction of competition and the subsequent erosion of monopoly profits, being only rational under strategic grounds[1]. In these circumstances, the licensing decision must be evaluated in the framework of the firm strategy (Fosfuri, 2004). Leaving apart these strategic cases, licensing offers the possibility to obtain direct revenues from technologies only exploited in some markets or not exploited at all by the patentholder, as the management literature has recently pointed out (Rivette & Kline, 2000). In such cases, whereas the licensing strategy is undoubtedly part of the firm strategy, the

[1] Arora et al. (2001) and Arora and Fosfuri (2003) suggest strategic reasons that can motivate licensing: to establish a technology standard, to expand quickly or to limit the effect of competing technologies.

decision to license each particular technology follows then a transaction-based approach (Williamson, 1991).

In this paper, we use the transaction costs approach to analyse the licensing decisions not motivated by strategic means of firms with development capabilities. In particular, our aim is to characterize the type of technologies that firms license in order to obtain extra revenues out from their technological portfolio. In order to achieve this objective, we rely on a sample of firms that decide to license some of their innovations in a technology marketplace that can be assumed, given its characteristics, to capture non-strategic licensing or, as we will put it, *pure revenue licensing*.

Research on markets for technology has mainly focused in *strategic licensing*. The characteristics of the markets that vehiculate these transactions and the firm´s incentives to license have been the main topics analyzed (Arora et al, 2001). On the contrary, literature has not paid attention to *pure revenue licensing*, partially because such type of licensing has not been prevalent at all in the strategy of technology-based firms. This trend seems to reverse. Rivette and Kline (2000) have underlined the potential of this type of licensing by looking at some figures. They draw attention to the fact that a considerable amount of firms have more than one third of underused technology assets that might be profitable in other hands. The potential to find *alternative* uses for some *existing* technologies is backed by facts such as the increasing interdisciplinarity of technologies across sectors (Elton and Voyzey, 2002) or the amount of new technologies that are just a recombination of existing ones.

The analysis of licensing practices is relevant from a firm perspective as well as from a public policy perspective. Given that research projects are extremely costly and risky, markets for technology can provide a two-fold advantage to technology intensive firms. On the private side, licensing allows firms to extract more revenues out from their costly research projects. From the social point of view, licensing enables firms to profit from technical solutions attained by others, reducing the bulk of duplicative inventive activity. Pure revenue licensing can contribute with a relevant share to the development of the market for technology and to the minimization of the existing inefficiencies.

In this paper, we observe a marketplace for technology that is likely to capture pure revenue licensing transactions: an Internet-based marketplace for technology. We examine the innovations that firms in the Chemical and Biotechnology sector offer for license or sell in this marketplace. Our aim is to explore the type of technologies that firms consider suitable for pure revenue licensing. In particular, we estimate how different dimensions that characterize an innovation in the firm's portfolio affect the likelihood that it is licensed with this purpose. This is the first study that analyses licensing practices from this perspective. This approach is specially suitable for the study of pure-revenue licensing, where the decision of the firm is mainly driven by the features of the innovations. Put in another way, the motivations that lead firms to license for pure revenue reasons are largely reflected in the characteristics of the innovations chosen. Therefore, the availability of data at the technology level is particularly valuable in the study of this type of licensing. We focus on patent intensive sectors, where we can rely on patent information to characterize individual innovations. Hence, the contribution of this paper is not only to shed light on pure revenue licensing but to do it using a new methodology in the analysis of licensing practices, that is, linking the characteristics of an innovation with the likelihood of being licensed.

The paper is organized as follows. Next section develops the theoretical background and the following, the hypotheses. In the fourth section, we explain the methodology used. The fifth section presents the empirical results and the sixth concludes.

2. MARKETS FOR TECHNOLOGY

2.1. Traditional Markets for Technology

Arora et al (2001) describe the Market for Technology as the markets for the exchange of intermediate technological inputs. Given the characteristics of the market and the characteristics of the assets transacted, the Market for Technology is characterized by many transaction costs. Such costs are defined as the costs derived from coordination between the partners of the transaction and their potential opportunism, known in the transaction costs literature as *coordination* and *motivation costs* respectively. Coordination costs arise from the fragmentation across sectors and geographical regions (Arora et al, 2001), that makes prohibitively costly technology transactions between partners of different regions or sectors. Technology transactions are particularly vulnerable to motivation costs, originated by opportunistic behaviour. For one reason, the asset object of the transaction, knowledge, is of a specially complex and intangible character. The context dependence of knowledge makes it difficult to transfer technologies outside of the particular domain –firm and application- where they are developed for (Arora et al, 2001). This problem sharpens when knowledge is more tacit and less codified, since, in such cases, information assymmetries and uncertainty are higher. Asymmetric information affects both licensor and licensee. The potential licensee is concerned about the value of the technology and the licensor's willingness to transfer the know-how. The potential licensor is concerned about the ability of the licensee to exploit the technology. As well, she cares about moral hazard problems that can arise from information disclosure. Disclosure may induce the licensee not to pay for using the technology once he has learnt the information. Or, even if he does not act opportunistically during the contract, he may then use the information he learnt to compete later with the patent holder in the technology market or in the final market (through imitation, for instance), especially when the boundaries of patents are not clear-cut. Moreover, licensing increases the disclosure of the technology. All these concerns are reflected in the costly negotiation (in terms of money and time) of licensing contracts and in the high percentage of deal abortions.

Technology transactions would be more efficient to the extent that the mentioned costs could be reduced. One means to reduce motivation costs is intellectual property rights protection (Arora, 1995), that is, to patent the technology object of the transaction. Firms used to transact with technology –patented or not- rely as well on contractual and institutional responses such as long-term or repeated contracting[2], reputation building (Arora et al, 2001), the use of middlemen[3] or patent pools (Merges, 1996). These mechanisms, however, are only effective in settings of repeated interactions such as sectorial and geographical networks of relationships that allow to build up reputation or to apply credible threats to punish opportunistic behavior. As a consequence, the minimization of transaction costs comes at a price, that is the restriction of the market to

[2] Anand and Khanna (2000) report that 30% of the licensing deals are signed between firms having prior relationships.
[3] The agents in the 19h century (Lamoreaux and Sokoloff, 1998), the nowadays consultant firms or the Specialized Engineering Firms (SEFs) in Chemicals.

the firms that are part of the mentioned networks. Firms outside them are left out of the market, since transacting with them is much costlier.

In strategic licensing, it is worth to pay this *price* in order to minimize motivation costs. In this case, the technology holder is very concerned about controlling the licensee's ability and incentives to exploit the technology, since it is a key piece of the firm strategy. Moreover, strategic reasons usually involve firms within the boundaries of the own sector and region. On the contrary, in pure revenue licensing, the main concern for the technology holder is to find a potential licensee rather than controlling potential opportunism. However, attractive targets as licensees for pure revenue licensing, such as firms from a different sector, region or market niche, small firms or start-ups, do not typically form part of the established networks and are very difficult to reach through traditional technology markets. Therefore, the restrictive set-up that characterizes these markets for technology poses an important drawback to pure revenue licensing transactions.

Consequently, pure revenue licensing would be more efficiently captured by a marketplace which main focus was to reduce coordination costs between the technology holder and suitable licensees for this kind of transactions. Motivation costs, even though not so stringent as in strategic licensing, should not be misconsidered in order to assure that potential deals are feasible. Markets for Technology did not shelter a marketplace with these characteristics up to now. However, the Internet offered recently an opportunity to build it. The Internet appeared in the nineties as a platform to reduce coordination costs in many markets, included business-to-business markets (Garicano and Kaplan, 2001), thanks to the easy and low cost access all over the world.

2.2. The Internet Market for Technology

The Internet offered the possibility to provide the market for technology with a marketplace where the costs of searching for potential licensees and technologies were virtually absent. By 2000, some websites were created with the aim to capture partners and technology transactions left apart in traditional industry licensing networks. Each of them targeted a different niche of the technology market, with litte success[4].

We focus on *yet2.com*, one of the websites devoted to technology transfer on the Internet that relatively succeeded to build a marketplace for technology. It was born from frustrations in the licensing of innovations of a former executive at Du Pont. The aim was to create a supra-regional and supra-sectorial marketplace for patented technologies, based on the negligible cost of access to the marketplace for potential partners. The other important feature of the marketplace was transparency in the display of information[5]. *yet2.com* built upon well known research intensive corporations as suppliers of patent protected technologies. This feature and the fee structure established[6] help to alleviate the adverse selection problems that potential licensees could otherwise face. However, no mechanism protected technology holders in front of potential opportunism by licensees. This is the reason why we assume that patent holders will use

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[4] Actually, many of the websites did not survive a long time. The ones that did, report a very low rate of deals signed. These are *Delphion*, a spin-off of IBM born to facilitate the licensing of IBM technologies, *yet2.com*, founded by a DuPont executive and *techex.com,* born from Yale University in order to commercialize university patents.

[5] Transparency is achieved by a more extensive and accurate description of the uses of the technology, beyond what is provided in the patent document, and a classification of the technologies according to their potential applications. This information (joint with the notice of being for license) differentiates these databases from the patent databases (mainly by the Patent Offices) available on-line.

[6] Site revenues come from access fees and a success fee over realized transactions. Patent holders listing technologies have to pay to do it. Searchers of technologies can search for free but they must pay in order to contact the owner of the technology.

this market only for transactions that do not entail meaningful motivation costs. As previously argued, this would be the case of licenses motivated by pure financial reasons. Therefore, *yet2.com* provides us with an opportunity to observe the responsiveness of firms to a change in transaction costs with respect to their licensing practices. Indeed, we can observe the technologies whose owners are willing to license in a set-up with negligible coordination costs and potentially huge motivation costs. This “experiment” sheds light on the motivations that induce firms to license for pure revenue reasons. Results will contribute to a deeper understanding of this unknown parcel of the management of innovation at firms. From an aggregate perspective, results will as well provide evidence on whether a market for pure-revenue licensing has potential to be developed and, in such case, how it ought to be designed efficiently.

3. HYPOTHESES

Since pure-revenue licensing decisions are not strategically motivated, we can essentially consider them technology-based choices. Then, the characteristics of the innovation have a direct effect on the adoption of the development strategy. We hypothesize then that technologies that firms devote to this purpose should present some differential attributes across firms and strategies.

Technologies can be characterized along different dimensions that reflect aspects such as the quality or the type of innovative contribution they embody. As well, we can describe them with respect to the rest of the firm’s technologies and knowledge. To sum up, we can characterize an innovation along *importance*, *radicalness, scope*, *complementarity* and *fit*, dimensions that can affect the likelihood that it is licensed for pure revenue purposes. In this section, we develop the hypotheses that link these characteristics with the mentioned likelihood. These hypotheses refer to established firms, with research and commercialization capabilities in a sector with an active traditional market for technology such as the chemical. These characteristics guarantee that they have different options available in order to exploit their technologies, which range from in-house development to different licensing strategies.

One of the most significant dimensions of an innovation is its **importance**, that is, the relevance it acquires into the scientific community. Some research using patent protected technologies shows that scientific value is positively correlated with the private value of the innovation, which translates into economic value for the patent holder (Harhoff et al., 1999; Hall et al. 2000). Consequently, the firm has stronger incentives to protect important patents. This implies, everything else equal, that the firm is more reluctant to license an innovation the more important it is (Katz and Shapiro, 1985). The reason lies on the high motivation costs that such innovations anticipate in case of license. On the one hand, the incentives for misappropriation by potential licensees or competitors increase when the prize of doing it increases. On the other hand, the cost the patentholder should bear in case of misbehaviour of the licensee or leakage of information increases with the scientific value of the innovation. These situations are especially acute when there is no institutional mechanism to control the licensee, as it happens in pure-revenue licensing. In such case, even if the leakage of information would occur in another market or region, it could damage the firm in its original market as well. Therefore, it is not likely that important innovations are subject to pure revenue licensing.

Innovative or radical innovations, as their name suggest, represent a breakthrough with respect to previous technologies. For an established firm, the implementation of such innovations means a rupture with the traditional line of the firm. Not only existing assets and capabilities are useless to undertake them but their introduction may also destroy existing business of the firm -through market cannibalization[7]-. Entrants, with no developed skills or markets, are more likely to introduce radical innovations whereas incumbents prefer to implement marginal improvements of existing technologies (Henderson, 1993). Shane (2001) finds that entrepreneurs are more likely to pick up more innovative patents in order to set up a new firm. These findings suggest interesting implications for the evaluation of licensing practices involving innovative technologies. Since an established firm is likely to discard them for exploitation, she may consider licensing as a means to obtain profits from them. However, she will rule out this possibility if there is risk of market cannibalization. Only if the innovation falls (or it can be used) far away from the firm's core, where this risk mitigates, the patent holder will be willing to license the innovation.

Scope, or **broadness**, is a dimension that refers to the technological space the innovation covers. If the technology is patent protected, scope is the technological area the patent protects from infringement[8]. Actually, scope is an intrinsic feature of the innovation –given by characteristics such as basicness- that is also determined by how inventors -or their lawyers- "design" then the patent, i.e. by the legal description of the

[7] In the adoption of an incremental innovation, the firm is likely to replace the old technology for the new one, eliminating therefore the potential cannibalization. On the contrary, if she adopts a radical innovation, it is too risky to abandon the old technology. Therefore, the two technologies coexist, with the subsequent potential for cannibalization.
[8] The broader the scope, the larger the number of potential products that will infringe the patent, as Merges and Nelson (1990) put it.

innovation[9]. Firms have incentives to maximize the *legal* scope because it maximizes the legal protection around the innovation. For instance, Shane (2001) finds that broadness confers an extra protection that is especially valuable to entrepreneurs meanwhile they acquire the assets they need to develop the technologies. Lerner (1994) finds that broader patents protect more important inventions[10]. Whereas both findings suggest that broadness is associated with protection, the causality between protection and value is not clear[11]. Nevertheless, this strong legal protection is considered worthwhile in licensing transactions (Arora and Gambardella, 1994 and Anand and Khanna, 2000), especially when the risks involved increase, such as in pure-revenue licensing. Scope is not only related to protection but also to the number of potential applications that can be developed from the technology. First, the more generic a technology is, the more products can be potentially derived from it[12]. Second, the coverage of a broader technological space offers more possibilities to develop the innovation protected from competition. The wider this technological area, the higher the likelihood that the patent holder is not present or interested strategically in all the applications protected by the property right. This fact opens the door to pure-revenue licensing. Therefore, the extra protection and interdisciplinarity of a broad innovation turn more likely that a broad innovation is licensed and, in particular, that it is licensed for pure revenue purposes.

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[9] *Legal* broadness is achieved by a generic description of the technology, in a way that the patent protection builds a wall around the particular technology of interest. Of course, Patent Office examiners are then the responsible to accept or refuse the invention as described, controlling the incentives of firms to design broader patents.

[10] He finds that broader biotechnology patents are more likely to be cited and litigated (two measures used to proxy for importance) and firms holding them receive larger valuations in the venture capital investment process.

[11] The first case suggests that broadness confers an extra value to the innovation whereas in the second, it is a mean to protect a valuable innovation.

[12] Think, for instance, of a basic innovation such as the laser, that has a huge variety of uses.

Complementary innovations denote technologies that result from a research process characterized by the combination of different types of know-how. The higher the number of knowledge sources that take part in the research process, the higher the degree of complementarity of the innovation. The existence of multiple sources of knowledge is relevant from the perspective of the transfer of information, especially when knowledge moves outside the firm as in the case of licensing. Usually, this knowledge is only embodied partially in blueprints, fact that requires the involvement of the creators of the innovation in the technology transfer process. In fact, this is a critical step in licensing deals. The degree of complementarity of the innovation plays an important role in this phase, since coordination costs increase with the number of information sources. This is a drawback for the potential licensee that may cause a deal abortion. Anticipating it, the technology holder may be reluctant to license such innovations. This fact will be especially true in non-strategic licensing, where the technology holder has few incentives and mechanisms to devote resources in order to overcome this problem.

Strategic fit is the degree to which the innovation fits into the core activities of the firm. It is widely known that established firms develop organisational and technical capabilities associated with their core. As a result, they are much more efficient to exploit opportunities within these boundaries than outside them. This is the reason why an innovation that fits the firm´s complementary assets is more likely to be developed by the firm. Licensing is less likely, due to the high risks that the disclosure of core information involves -except if it obeys to strategic reasons-. Conversely, innovations that fall out of the firm’s core are more likely to remain unexploited by the firm, leaving the door opened to licensing for pure-revenue purposes.

4. EMPIRICAL MODEL

We would like to estimate the probability that a given patented innovation is licensed for revenue purposes. Each observation represents a patent. The outcome variable is a binary dependent variable that captures the decision by the firm whether or not to offer a patent for pure revenue licensing[13]. We should therefore use a discrete choice model with the following specification for patent *j* in firm *i*:

$$Y^*_{ij} = \beta' X_{ij} + \varepsilon_{ij} + \alpha_i \qquad \text{where } \begin{cases} Y_{ij} = 1 & \text{if } \quad Y^*_{ij} > 0 \\ Y_{ij} = 0 & \qquad\; Y^*_{ij} \leq 0 \end{cases} \qquad j = 1,2,\ldots N_i \;;\quad i = 1,2,\ldots I$$

where Y^*_{ij} denotes the unobservable propensity that it is licensed for revenue purposes, X_{ij} is a vector of patent-varying exogenous variables, ε_{ij} is the unobservable error term and α_i is a variable that captures the firm specific unobserved effects. Therefore, we assume that the incidence of pure revenue licensing is only observed when the patent's propensity to be licensed for such purposes is greater than a threshold equal to zero. The α_i variable should be introduced to the model given that we can not assume independence on the error terms. Since there are many patents in the sample owned by a given firm *i*, each firm represents a cluster of correlated observations. The dilemma is whether α_i should be treated just as a constant term over firms (fixed effects model) or as a random variable just like the error term (random effects model). The latter approach obtains more efficient estimates but it requires the assumption that the α_i 's are independent of the X_{ij}'s if our estimates are to be consistent. The Hausman test allows testing this assumption (Maddala, 1993). We do not find conclusive evidence for the rejection of the null hypothesis of consistency of the random effects model. Moreover, we are interested in including some firm-invariant variables (z_i) such as the size of the

[13] Note that zeros include either strategic licensing, own development or no use.

firms' patent portfolio. In this case, if we used the fixed effects model we could not estimate their parameters (γ), because α_i captures the effect of all the firm-invariant variables. Therefore, we treat α_i as random. The specification is as follows:

$$Y^*_{ij} = \alpha_i + \beta' X_{ij} + \gamma' z_i + \varepsilon_{ij}$$

The probit model is the most appropriate discrete choice technique to estimate it. The multivariate normal distribution in which it is based upon is more flexible than the multivariate logistic distribution (Maddala, 1993). Therefore, we use a probit random effects model.

5. DATA AND MEASURES

The data we use comes from two sources. First, we identify firms[14] being customers at *yet2.com,* the main website devoted to the transfer of patented technologies between firms at the time of data collection. For these firms, we collect data on the patents that they offer on this Internet marketplace. We assume that each patent proxies for an innovation[15]. We restrict our attention to firms that offer innovations under the categories of *Chemicals* and *Biotechnology* that also fall in these categories according to the United States Patent Office (USPTO) classification[16]. We end up with 905 patents granted to 89 different firms. Second, we use the NBER Patent Citations Data File

[14] We do not take into account governmental agencies or research institutes, since they may have other motivations to license than firms with development capacities.

[15] This assumption implies that we take for granted that one innovation is protected by one patent. This is not necessarily the case: the number of patents that cover an innovation depends mainly on the sector. As Cohen et al (2000) point out, in chemicals a technology is protected by a few number of patents while in electronics, for instance, the number can reach hundreds. Even though data is available at *yet2.com* at the innovation level, we are not able to use this information for practical reasons in our empirical analysis – we can only build a control group at the patent but not at the innovation level-.

[16] The USPTO assigns the patents to a primary and some secondary patent classes. Hall et al (2001) have established a correspondence between classes and industrial sectors. We use the primary class of a patent in order to assign its correspondence to an industrial sector.

(Hall, Jaffe & Trajtenberg, 2001) to identify the population of chemical and biotechnology patents granted from 1982 to 1999 by the USPTO to this set of patent active firms. From the population of patents that are not present in the Internet licensing marketplace, we draw a 10% random sample (8364 observations) that composes the control group[17]. The NBER database contains very useful information at the patent level -application year, granted year, primary sector, number of citations made and received, and other primary and constructed variables-, that we use to characterize the innovations.

5.1. Variables

The **dependent variable** reflects whether the patent is offered in the Internet licensing marketplace. We use patents to proxy for innovations. Patents are coded 1 if identified as being offered in *yet2.com* and 0 otherwise. The observations coded zero sum up to 8364 and represent the control group. There are 905 observations coded as 1, which represents approximately ten percent of the total. **Relevant explanatory variables** are described next.

Recent literature has suggested as proxy for **importance** the ***number of citations a patent receives*** from subsequent patents. When inventors patent some innovation, they must cite the previous inventions their innovation builds upon. Therefore, citations received from subsequent patents reflect the contribution to science of a given patent (see Jaffe et. al 2000 for evidence from a survey). Different authors have tested the link

[17] The population that constitutes the comparison group sums up to 61000 patents. Random sampling is used in empirical works (Hu, 2003) involving comparison between different patent groups. Alternatively, matching samples are also used (Trajtenberg et al, 1992).

between this proxy and different measures of value such as social value (Trajtenberg, 1990), stockmarket value (Hall et al., 2000) or commercial value of the innovation as perceived by the patentholder (Harhoff et al., 1999). Citations present a practical problem: since data is truncated at a certain point in time, patents granted closer to this truncation data have a shorter time span to receive citations[18]. In order to remove variance due to truncation, we standardize the data using the method proposed by Hall et al. (2001)[19]. Alternatively, we simply introduce year dummies[20].

We measure the degree of **innovativeness** with the amount of ***citations*** the patent ***made*** to previous patents. The lower the number of citations made, the less derivative in nature the patent is, i.e. the less it builds upon previous research (Lanjouw & Schankerman, 1999) and the more innovative it can be considered. We can as well proxy innovativeness by ***originality***, a Herfindhal-like index that measures the concentration of citations across patent classes. If citations are spread across different classes, the invention is not a mere sequential innovation but it “breaks molds” (Hall et al, 2001). In order to measure innovativeness within the firm, we can use the percentage of citations made to previous patents by the same firm, the ***self-citations made***, with respect to the total number of citations the patent makes. A low percentage indicates that the innovation represents a new step in the research line of the firm.

There have been different attempts to measure **scope**. The most widely used (Lerner, 1994; Shane, 2001; Reitzig, 2001) is the number of patent classes a patent is assigned

[18] A patent receives only 50% of its citations in ten years from its granted date (Hall et al, 2001)

[19] This method consists in standardising the citations received by year and sector. As the mentioned authors warn, this method also removes variance due to real effects. We believe, however, that this problem is actually negligible if we work with a group of patents from the same sector (chemicals and biotech) with a quite homogeneous citation pattern.

[20] Shane(2001) uses also this method. Henderson et al (1998), for instance, use the standardization method.

to, as a proxy for the number of potential sectors of activity in which the patent can be applicable. Instead, we use a Herfindhal-type concentration index of citations received across patent classes, ***generality***[21], as suggested by Trajtenberg et al (1992). They suggest that the spread of citations received across classes proxies the technological space the patent actually covers. Therefore, the higher the generality, the higher the scope. An alternative measure suggested by Lanjouw & Schankerman (1999) that we use is the number of ***claims,*** the sentences that describe an invention. They can be interpreted as "units of invention" (Jaffe, Hall & Trajtenberg, 1999) and the higher its number, the broader the technological space covered[22].

We measure the degree of **complementarity** of an innovation through the ***number of inventors*** that participate on it. Teams of inventors are regarded as a key mean for knowledge exchange (Breschi et al, 2002). Therefore, a co-authored innovation is the result from the interaction between different sources of complementary know-how.

We measure **strategic fit** through ***self-citations received***. Self-citations refer to citations received from patents owned by the same firm. In parallel with citations received, self-citations received reflect the importance of the innovation within the firm. The more the research of the firm builds upon a certain innovation by the same firm, the more likely it is a key technology. An alternative measure we use to assess the fit of a patent in the strategy of the firm is the relative weight of its patent class in her patent portfolio. Following Song et al (2003), we construct a dummy variable, ***core***, that captures

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[21] $Generality_j = 1 - \sum_k^{n_j} s_{jk}^2$, where s_{jk}^2 = percentage of citations received by patent j that belong to patent class k out of n_j patent classes

[22] Reitzig (2001) suggests that this measure can be highly endogenous, since the firm decides how to break down the actual blocks of invention. However, firm discretion is constrained to a great extent by the type of technology and by Patent Office examiners.

whether the patent class of the innovation coincides with the highest frequent classes in the firm's portfolio[23].

We use the following control variables: size, diversification[24], time and technological category. These characteristics may affect the firm's decision related to licensing as well as the characteristics of her patents and innovations. **Size** is meant to control for experience in managing intellectual property, access to traditional licensing networks and bargaining power in licensing negotiations. The most appropriate measure in this setting is ***patent portfolio,*** the number of patents granted by the USPTO to the firm in the previous years (1982-1999). **Diversification** means potentially more interdisciplinary innovations, opportunities to exploit them and accessible licensing networks. In order to determine the degree of diversification of a firm, we compute the measure proposed in Davis et al. (1994)[25]. The **time** control is required because all citations or citation-related variables are time-dependent. We use the ***application year*** of the patent. Finally, we control for **technological category** because the majority of the independent variables vary with technological field. Technological categories are built upon patent classes (Hall et al., 2001).

Table 1 presents a summary of the variables. Note that the different proposed proxies for some of the latent variables capture different dimensions of them[26]. We report in **Table 2** the **descriptive statistics** for the set of patent data that we will mainly use in

[23] We consider them as the patent classes that represent more than a 10% of the firm's portfolio at the five-year time span before the decision of commercialization in the Internet (1995-1999). If we consider core patent classes those that represent a 20% of patent share, results do not change.
[24] The latter two measures are available only for a certain set of firms (public US-based firms with more than $10 millions in assets and 500 shareholders).
[25] It takes the form $\sum p_i \ln(1/p_i)$, where p_i is the proportion of the firm's sales made in segment *i*. We retrieve this information from the Form 10-K filed with the Securities and Exchange Commission (SEC).
[26] Looking at their correlations (Table 3), we can appreciate that we will not suffer from multicollinearity problems.

the regression analysis: 89 firms and 9269 observations. We include a t-test for differences of means for the two patent groups across the proxies of the invention dimensions. We can appreciate significant differences for all the variables except for *citations received* and *generality*. This fact anticipates that the two groups of innovations differ significantly. In **Table 3** we present the correlation between the variables used as regressors. Many of them present a significant correlation at a one percent level. However, the highest correlation coefficients do not suggest the presence of multicollinearity problems, as it is confirmed by high tolerance levels[27].

6. EMPIRICAL RESULTS

Table 4 presents the marginal effects (at the median) of the different variables on the probability that the patent is offered by pure-revenue licensing[28]. Such effects have been obtained from a random effects model, where the independent variables have been log transformed in order to reduce their skewness[29]. We test six different Specifications

Specification 1 includes one proxy per each of the four magnitudes describing the characteristics of the patented invention. In particular, we introduce only the variables that represent raw information from the patent: number of *claims* describing the invention, number of citations received *(creceived)*, number of citations made *(cmade)* and number of inventors *(inventors)*. Overall, the model is significant. The proportion of the total error variance accounted for by the random effects is significant (rho=.339,

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[27] The highest correlation level is ρ =.5057 and it appears between *citations* and a variable built upon it (*generality*). The lowest tolerance level is .73.

[28] We compute the marginal effect at the median of the log transformed variable in order to easily identify the original value it corresponds to (i.e. the median of the original variable).

[29] In order not to lose observations with a zero value when taking logarithms, we add up one to the original variable before doing the transformation.

p<.000). The magnitude of the effect of each variable is reflected by the percentual increase in the likelihood (indicated by the marginal effect) when its value increases a 1% from its median, with the rest of variables kept constant at their median. *Creceived* displays a non-significant positive coefficient, contrary to our prediction. The coefficient on *cmade* displays a significant negative sign, which supports the hypothesis that more innovative patents are more likely to be the object of pure revenue licensing. *Claims* has an as predicted positive but not significant coefficient. *Inventors* displays a positive and highly significant coefficient, suggesting that the more complementary the innovation, the more likely it is to be licensed for pure revenue purposes –contradicting our initial prediction-. We also include a dummy, *core,* that captures the effect of the strategic fit over the likelihood, negative and non-significant in this case, fact that suggests that core innovations are less likely to be licensed for pure revenue purposes. We control for *portfolio*, that displays (and it will do across all specifications) an as predicted negative sign.

In **Specification 2, 3** and **4,** we include variables that are derived from the citations, *selfcitations*, *generality* and *originality*. Their introduction shows the robustness of the effect of the different variables on the likelihood. The coefficient on *selfcitations received*, although not significant, strengthens the negative effect of *strategic fit*. The estimated effects of *selfcitations made* and *originality* reveal a positive impact of innovativeness. The coefficient on *generality* supports the idea that broader patents show up more likely on pure-revenue licensing markets. Finally, *creceived*, the proxy for importance, turns to the predicted negative sign, even though it remains non-significant.

Specification 5, 6, 7 and 8, gather the effect of some interesting interactions. We find significant the interactions between fit (*core*) and both innovativeness (*self citations made*) and importance (*creceived*) as well as the interaction between the latter and complementarity (*inventors*). The negative effect of the variable that reflects importance becomes significant and, strikingly, it turns positive when the innovation belongs to the firm's core. This evidence suggests that whereas an important innovation in the core is more likely to be licensed for pure-revenue purposes, the reverse holds if the important innovation is out of the core. Therefore, it should exist some underlying difference between important innovations in and out the core. As mentioned, the more important the invention and the better it fits the firm strategy, the more likely it is to be developed by the patentholder. In this context, pure revenue licensing can be understood as a complementary way to exploit an innovation with high potential for economic revenues. When the important innovation is not in the core, lack of information or contractual restrictions with a potential licensee who would exploit the innovation may turn pure-revenue licensing less likely.

The rest of the interactions also display interesting results. The positive effect of importance in the core is even stronger if the innovation shows a high degree of complementarity. Actually, the effect of complementarity turns significant only when the innovation is important. The interaction between fit and innovativeness within the firm suggests that the more innovative technologies from the core are actually less likely to be licensed than less innovative ones in this same situation. This result confirms our prediction on the lack of incentives to license radical innovations due to the potential for cannibalization.

In **Table 5** we display results for a sample restricted to 22 big US firms according to the value of their assets and the number of their shareholders[30]. For these firms we have available data on diversification, a firm-variable that can be relevant in explaining pure-revenue licensing. Indeed, this variable has a significant positive effect on the likelihood. This result may suggest that diversified firms have a more proactive licensing policy –due to a higher awareness of the benefits of pure-revenue licensing- or/and a higher rate of underused patents. The inclusion of this control does not lead to significant changes in the effect of the rest of the variables. There are, however, some changes due to the restriction to the sample of big firms. The reduction in sample size affects the significance of the *claims* variable and the interaction between importance and complementarity. On the other hand, the effect of *selfcitations received* becomes significant, suggesting that the negative effect of this variable comes from large firms.

Table 6 presents an estimation including only the variables that are known at the time of patent application. The purpose is to test whether the information contained in the patent has any predictive power at that moment. It actually does. Innovativeness, complementarity and strategic fit point significantly towards the same direction that they do when there is more information available (basically, after some time span that allows to receive citations). Therefore, at the same moment of the patent application, it can be predicted whether a patent is more or less likely to be licensed for pure-revenue purposes.

To sum up, results confirm that the likelihood that an innovation is licensed for pure-revenue purposes depends to a certain extent on the characteristics of the innovation. In

[30] These are firms identified in the Compustat database, that provides complete information on public US-based firms with more than $10 millions in assets and 500 shareholders (obliged to report to the SEC)

particular, we find support for our hypotheses on the negative effect of importance and strategic fit and the positive impact of innovativeness and scope. The unexpected positive effect of complementarity could be related to the stronger protection that this dimension may confers to the licensor. Actually, when know-how comes from different sources, it is easier to protect it from the licensee. Another unexpected result, the positive effect of important innovations in the core, reflects the potential of these technologies of being licensed for pure-revenue reasons as a complement of own development.

7. CONCLUSION

In this paper, we examine the firm’s decision to license patented innovations with the only purpose of extracting revenues. The strategic considerations usually present in technology licensing are absent in these cases. Of course, these licensing decisions belong to the firm’s strategy, which will have as one of its objectives to profit from its innovations through licensing. We can think of these innovations object of pure-revenue licensing as underexploited technologies. Such technologies are either completely unexploited or, at least, not exploited in all possible uses or markets. Indeed, nowadays, in firms’ portfolios there are many patents that remain unexploited (they are known as *sleeping patents*) as well as highly interdisciplinary technologies.

Our aim is to characterize the pure-revenue licensing market. Due to the particular motivations behind these licensing decisions, we argue that the transactions captured by this market should differ from the mean firms’ technology. Thanks to the patent information, we are able to characterize different dimensions of the innovations. The underlying assumption is that the features of the technologies reveal information on their potential uses and, indirectly, on the probability of being licensed.

Our findings suggest that, indeed, a patent devoted to pure-revenue licensing differs significantly from the mean patent on the firm's portfolio along different dimensions. The dimensions that affect positively the likelihood of being licensed for pure-revenue purposes are innovativeness, scope and degree of complementarity of the patent, as well as importance if the technologies are in the firm's core. Actually, these innovation features reflect an increasing likelihood of being underused innovations, which favors pure-revenue licensing. On the other hand, importance (except when in the core) and core (except for important innovations) affect negatively the likelihood that the innovation is licensed for pure-revenue purposes. These dimensions reflect concerns for value appropriation in licensing. Results, therefore, increase our understanding on the drivers of licensing decisions in a setting where strategic concerns are left aside.

We believe our findings to be relevant in another aspect, as well. They suggest that transaction costs involved in technology transfer do not affect equally all potential transactions. In particular, some characteristics of the markets for technology may prevail over others according to the motivations for licensing, the characteristics of the licensed technology and the characteristics of the patent holder. A patent holder does not need for any technology transfer transaction the protection that the network offers in traditional licensing markets through the control of licensee's potential opportunism. Instead, in some cases, she might prefer a contact-network that minimizes the costs of searching for a licensee, who enables her to extract revenues from underexploited technologies. This is a relevant distinction with respect to the implications for the development of efficient markets for technology. Pure-revenue licensing could arise as a first step in the development of such markets. Results do not only illustrate the need for differentiated markets for technology. They suggest as well that firms are aware of their stock of underexploited technologies and they are willing to adopt a proactive licensing policy. Obviously, this awareness is only the first step in the development of a pure-revenue licensing marketplace. There is then the need to evaluate whether it exists a demand that could absorb this supply of technology and which are the best mechanisms to attract it. Only then we could be able to design an efficient pure-revenue licensing market that solves the inefficiencies associated with the stock of underexploited technologies.

Finally, we believe that results from this analysis suggest very interesting avenues for future research in technology transfer. As mentioned, it is a must to extend the analysis to the demand side of the licensing market and be able to come out with a proposal on the design of a marketplace that would vehiculate pure-revenue licensing transactions efficiently. Secondly, it would be interesting to conduct a parallel analysis to explore the characteristics of the innovations that are licensed for strategic reasons. Then, we would be able to understand better the black box of technology licensing in firms.

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Appendix

Table 1. Summary of variables

Variable name	*Description*	*Proxy*	*Expected effect*
Citations received	Number of citations the patent receives from subsequent patents	Importance	-
Citations made	Number of citations the patent makes to previous patents	Innovativeness	-
Originality	Herfindhal index on the spread of citations made to different patent classes	Innovativeness	-
Self-citations made	Share of citations made to patents by the same firm	Innovativeness	+
Claims	Number of sentences describing the invention	Scope	+
Generality	Herfindhal index on the spread of citations received from different patent classes	Scope	+
Inventors	Number of inventors listed in the patent	Complexity	-
Core	Dummy equal to one if the class of the patent is among the highest frequent (>10%) patent classes in the firm's portfolio (period 1995-99)	Strategic fit	-
Self-citations received	Share of citations received from patents by the same firm	Strategic fit	-
Application year dummy	Year in which the firm submits the patent to the Patent Office	Time control	n.a.
Category dummy	Technological category that corresponds to the patent primary class	Technological control	n.a.
Portfolio	Number of patents granted to the firm (in any technological category, 1980-1996)	Firm characteristic	-
Diversification	Diversification measure	Firm characteristic	-
Sales	Firm sales (in billions)	Firm characteristic	+/-

Table 2. Descriptive Statistics

VARIABLES	***Mean*** (N=9269)	***Min***	***Max***	***Mean Y=0***	***Mean Y=1***	***Difference of means*ζ**
Citations received	4.163	0	184	4.177	4.035	.1413 (.2657)
Citations made	8.041	0	161	7.916	9.193	-1.277*** (.3534)
Originality	.3782*	0	.9246	.3742	.4147	-.0405*** (.0102)
Self-citations made	.2256	0	1	.2302	.1828	.0474*** (.0106)
Claims	12.85	1	183	12.62	15.13	-2.508*** (.3937)
Generality	.2246	0	.9204	.2253	.2183	.0070 (.0100)
Inventors	2.952	1	16	2.943	3.029	-.0865* (.0625)
Core	.1834	0	1	.1803	.2121	-.0318*** (.1354)
Self-citations received	. 1745	0	1	.1773	. 1487	.0286*** (.0109)

ζMean comparison t-test on equality of means (H_0:mean(0)-mean(1)=0).
Significance level: .01***; .05**

Table 3. Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) *creceive*	--								
(2) *cmade*	.0634	--							
(3) *original*	.0573	.3644	--						
(4) *selfct*	-.011*	-.007*	-.0427	--					
(5) *claims*	.1379	.2051	.0961	.0113*	--				
(6) *general*	.5057	.0199	.1703	-.0423	.0884	--			
(7) *selfcd*	-.1391	.0500	-.0211	.1015	.0463	.1523	--		
(8) *inventors*	-.0571	-.0388	-.0638	-.014*	-.0305	-.0757	-.002*	--	
(9) *core*	.0270	.0821	-.0987	.0937	.0175*	-.0924	.1186	.0809	--
(10) *portfolio*	.0054*	-.012*	-.0144*	.1062	-.0246	-.0183*	.0629	-.0238	-0.044

*Significance level bigger than .05

Table 4: Probit Random Effects, Marginal Effects at the Median

Variables	Specif. 1	Specif. 2	Specif. 3	Specif. 4	Specif. 5	Specif. 6	Specif. 7	Specif. 8
Importance								
Citations received	.0009 (.0026)	.0014 (.0030)	-.0035 (.0031)	-.0042 (.0038)	-.0137*** (.0052)	-.0046 (.0038)	-.0124*** (.0050)	-.0187*** (.0045)
Innovativeness								
Citations made	-.0071*** (.0033)	-.0075*** (.0035)	-.0076*** (.0038)	-.0067** (.0041)	-.0067* (.0035)	-.0071** (.0042)	-.0063** (.0038)	-.0071** (.0039)
Originality			.0077 (.0116)	.0068 (.0134)	.0061 (.0142)	.0082 (.0137)	.0065 (.0124)	.0063 (.0123)
Self citations made		-.0369*** (.0155)		-.0378*** (.0159)	-.0433*** (.0183)	-.0494*** (.0196)	-.0354*** (.0148)	-.0448*** (.0173)
Scope								
Claims	.0040 (.0029)	.0046 (.0032)	.0040* (.0026)	.0062** (.0033)	.0065** (.0035)	.0063** (.0033)	.0057** (.0030)	.0047* (.0029)
Generality			.0257* (.0139)	.0309** (.0163)	.0458*** (.0192)	.0419** (.0211)	.0287** (.0151)	.0393*** (.0164)
Complementarity								
Inventors	.0140*** (.0053)	.0152*** (.0058)	.0127*** (.005)	.01276*** (.0056)	.0153*** (.0069)	.0129*** (.0058)	.0013 (.0054)	.0053 (.0056)
Strategic fit								
Core	-.0067 (.0058)	-.0044 (.0065)	-.0042 (.0053)	-.0049 (.0064)	-.0336*** (.0121)	-.0146** (.0082)	-.0043*** (.0059)	-.0298*** (.0102)
Self citations received		-.0071 (.0115)		-.0039 (.0110)	-.0077 (.0121)	-.0035 (.0112)	-.0037 (.0102)	-.0083 (.0106)
Interactions								
Core x Creceived					.0336*** (.0114)			.0272*** (.0091)
Core x Selfcitations made						.0589** (.0331)		.0509** (.0295)
Creceived x Inventors							.0096*** (.0042)	.0082** (.0039)
Firm controls								
Portfolio	-.0314*** (.0083)	-.0330*** (.0086)	-.0285*** (.008)	-.0273*** (.0075)	-.0221*** (.0088)	-.0277*** (.0076)	-.0254*** (.0072)	-.0295*** (.0082)
Controls								
Category	Included	Included	Included	Included	Included	Included	Included	Included
Application year	Included	Included	Included	Included	Included	Included	Included	Included
Rho	.3392***	.3253***	.3404***	.3068***	.3024***	.3045***	.3075***	.3430***
N	8611	8611	8581	8581	8581	8581	8581	8581
Groups	89	89	89	89	89	89	89	89
Wald χ^2 – test	334.77***	341.49***	339.28***	254.89***	296.30***	274.53***	268.59***	371.39***

For dummy variables, effect of a discrete change from 0 to 1
Standard errors of marginal effects in parentheses.
Confidence level of the coefficient (not marginal effect) at 1%***, 5%**, 10%*.

Table 5: Probit Random Effects, Marginal Effects at the Median. Large firms.

Variables	Specif. 1	Specif. 1A	Specif. 2	Specif. 2A	Specif. 3	Specif. 3A	Specif. 4	Specif. 4A
Importance								
Citations received	.0008 (.0065)	-.0001 (.0059)	.0047 (.0077)	.0032 (.0070)	-.0037 (.0091)	-.0047 (.0081)	-.0233** (.0110)	-.0120** (.0061)
Innovativeness								
Cmade	-.0141** (.0082)	-.0140** (.0077)	-.0156** (.0088)	-.0155** (.0083)	-.0184** (.0101)	-.0179** (.0094)	-.0178** (.0103)	-.0118*** (.0065)
Originality					.0273 (.0344)	.0246 (.0309)	.0243 (.0359)	.0139 (.0187)
Self citations made			-.0632** (.0336)	-.0597** (.0314)	-.0600** (.0322)	-.0561** (.0298)	-.0964*** (.0412)	-.0484*** (.0246)
Scope								
Claims	.0028 (.0071)	.0036 (.0066)	.0031 (.0077)	.0042 (.0071)	.0037 (.0072)	.0046 (.0066)	.0038 (.0076)	.0021 (.0039)
Generality					.0482 (.0383)	.0457 (.0345)	.0863** (.0435)	.0446** (.0244)
Complexity								
Inventors	.0364*** (.0137)	.0336*** (.0131)	.0396*** (.0146)	.0363*** (.0139)	.0491*** (.0188)	.0337*** (.0133)	.0415*** (.0153)	.0192*** (.0090)
Strategic fit								
Core	-.0150 (.0163)	-.0207 (.0152)	-.0049 (.0186)	-.0135 (.0166)	.0245 (.0311)	-.0073 (.0159)	-.0843*** (.0314)	-.0395*** (.0184)
Self citations received			-.0490* (.0321)	-.0475* (.0300)	-.0449* (.0303)	-.0430* (.0280)	-.0546** (.0332)	-.0305** (.0193)
Interactions								
Core x Creceived							.0634*** (.0225)	.0307*** (.0140)
Core x Selfcit. made							.1851** (.0974)	.0908** (.0557)
Firm characteristics								
Portfolio	-.0389*** (.0148)	-.0415*** (.0146)	-.0387*** (.0151)	-.2218*** (.0614)	-.0354*** (.0144)	-.0386*** (.0141)	-.0363*** (.0146)	-.0313*** (.0130)
Diversification		.0315 (.0203)		.0394* (.1506)		.0386* (.0211)		.0733*** (.0282)
Sales								
Controls	Included	Included	Included	Included	Included	Included	Included	Included
Rho	.3237***	.2922***	.3207***	.2861***	.3256***	.2861***	.3257***	.3626***
N	3850	3850	3850	3850	3838	3838	3838	3838
Groups	22	22	22	22	22	22	22	22
Wald χ^2 – test	89.44***	97.77***	96.40***	105.84***	98.62***	108.37***	122.30***	181.32***

For dummy variables, effect of a discrete change from 0 to 1
Standard errors of marginal effects in parentheses.
Confidence level of the coefficient (not marginal effect) at 1%***, 5%**, 10%*.

Table 6. Probit Random Effects, Marginal effects at the Median. Subset of known variables at time of patent application.

Variables	Specif. 1	Specif. 2
Innovativeness		
Citations made	-.0082** (.0035)	-.0088** (.0047)
Originality	.01212 (.0146)	.0139 (.0152)
Self citations made	-.04142*** (.0170)	-.0547*** (.0218)
Scope		
Claims	.0065** (.0035)	.0067** (.0036)
Complementarity		
Inventors	.0140*** (.0061)	.0145*** (.0067)
Strategic fit		
Core	-.0066 (.0068)	-.0173** (.0092)
Interactions		
Core x Selfcitations made		0648** (.0368)
Firm controls		
Portfolio	-.0299*** (.0076)	-.0306*** (.0078)
Controls		
Category	Included	Included
Application year	Included	Included
Rho	.3055***	.3017***
N	8581	8581
Groups	89	89
Wald χ^2 – test	252.35***	246.5***

Standard errors of marginal effects in parentheses.
Confidence level of the coefficient (not marginal effect) at 1%***, 5%**, 10%*.