Laboratory of Economics and Management
Sant'Anna School of Advanced Studies

Piazza Martiri della Libertà, 33 - 56127 PISA (Italy)
Tel. +39-050-883-343 Fax +39-050-883-344
Email: lem@sssup.it Web Page: http://www.lem.sssup.it/

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The Market for Patents in Europe

Alfonso GAMBARDELLA*
Paola GIURI**
Alessandra LUZZI***

* Bocconi University, Milan, Italy
** Sant'Anna School of Advanced Studies, Pisa, Italy
*** University Carlos III, Madrid, Spain

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Alfonso Gambardella[a], Paola Giuri[b], Alessandra Luzzi[c]

[a]IEGI, Bocconi University, Via Filippetti 9, Milan 20122, Italy.
agambardella@unibocconi.it
[b]Sant'Anna School of Advanced Studies, LEM, P.zza Martiri della Libertà , 33
56127 Pisa, Italy. giuri@sssup.it
[c]Universidad Carlos III de Madrid, Departamento de Economia de la Empresa,
Calle Madrid 126, 28903 Getafe, Madrid (Spain). aluzzi@emp.uc3m.es

Abstract

By using the PatVal-EU dataset we find that the most important determinant of patent licensing is firm size. Patent breadth, value, protection, and other factors suggested by the literature also have an impact, but not as important. In addition, most of these factors affect the willingness to license, but not whether a license actually takes place. We discuss why this suggests that there are transaction costs in the markets for technology. The issue is important because many potential licenses are not licensed suggesting that the markets for technology can be larger, with implied economic benefits.

Keywords: Licensing, patent scope, complementary assets, firm size, markets for technology
JEL: D45, O32, O34

1 Introduction

The importance of technology licensing has long been recognized by the managerial and the industrial economic literature. Early studies on licensing, especially in the industrial economic tradition, emphasized its implications for the diffusion of technology, the duplication of research, and product market competition (e.g. Shephard, 1987; Rockett, 1990; Gallini, 1984). Recently, there has been a revived interest in this topic in the managerial and technological literature. A natural reason is that technology licensing has increased considerably worldwide during the 1990s (e.g. Athreye and Cantwell, 2005) following a greater emphasis of company strategies on technology exchange through arms-length market transactions, strategic alliances, or cross-licensing agreements (e.g. Grindley and Teece, 1997; Rivette and Kline, 2000; Arora et al., 2001; Hall and Ziedonis, 2001; Arora and Merges, 2004; see also OECD, 2005, and *The Economist*, 2005).

This paper focuses on two issues. First, there is a fairly extensive literature highlighting several theoretical determinants of technology licensing. Yet, because of the limited availability of comprehensive data, practically no study has been able to provide in a single paper a broad empirical assessment of the theoretical factors that affect licensing as suggested by the literature. Second, existing studies have not been able to disentangle the determinants of the propensity to license vis-à-vis the actual occurrence of a licensing event. This is important because, as we shall see below, there is a fair share of patents that the owner would like to license but which are not licensed. These technologies may be of small or no economic value. Hence, they may have no demand. Alternatively, there could be transaction costs or other impediments to technology trade. If so, the markets for technology could be larger than what we observe. Since there are many unused patents, this could enhance the use of technology, and produce benefits associated with a greater utilization of technologies that would otherwise be under-exploited.

The PatVal-EU data (PatVal for short) enable us to achieve both goals. PatVal is described in detail in Giuri et al. (2005), also published in this Issue. It is based on a survey of the inventors of 9,017 European patents granted at the European Patent Office (EPO) between 1993 and 1998. The inventors were located in France, Germany, Italy, the Netherlands, Spain and the United Kingdom. A unique feature of our survey is that it provides information about whether the patent was licensed or not, and if not whether the inventor thought that the applicant was willing to license it. This information is usually largely unavailable, especially at the scale of this study. Furthermore, we combine the PatVal data with additional variables at patent and firm levels by drawing on other EPO and firm level datasets like Amadeus and Who Owns Whom. We can then perform a comprehensive analysis of the determinants of patent licensing at the micro level.

We divide our analysis into two steps. We first run a probit estimation of the probability to license a patent where we ignore the question of the propensity to license and focus on actual licensed patents. This is to show some plain results without the complications of the more elaborate structure of our second estimation. We discuss the main theoretical propositions in the literature on the determinants of technology licensing, and empirically test them in the same regression model. We corroborate the main theories and findings of the literature about the role of patent protection, complementary assets and the nature of knowledge. Moreover, we provide new evidence. We find that licensed patents are: a) broader in scope; b) correlated with measures of their economic value; c) more likely when they are owned by smaller firms. Existing empirical studies on technology licensing rely on small samples, and focus on specific industries like computer, semiconductors, and chemicals (e.g. Grindley and Nickerson, 1996; Grindley and Teece, 1997; Hall and Ziedonis, 2001; Cesaroni, 2003; Fosfuri, 2004; Kollmer and Dowling, 2004). The cross-sector studies by Anand and Khanna (2000) and Arora and Ceccagnoli (2006) are closer to the breadth of our work. However, we employ a richer set of explanatory variables.

In our second step we estimate a Heckman-selection model. We look at the determinants of the choice to license a patent and, given that the applicant is willing to license, at what determines whether the patent is actually licensed. PatVal itself provides the motivation for this analysis. While about 11% of the PatVal patents are licensed, for another 7% the owner was willing to license but did not, which suggests that the market for patents could be almost 70% larger. This links to another important issue about patents, viz, that many of them are not used. Some of them are not used for strategic reasons ("blocking" patents, e.g. Hall and Ziedonis, 2001). But others are not used because the owner does not have the resources, or the incentives, to invest in them. For example, a survey conducted by the British Technology Group (1998) revealed that 67% of US firms own technologies that they do not use. Similarly, Rivette and Kline (2000) show that large firms are repositories of unused patents.

While strategic patents are unlikely to be licensed in any case, an active market for technology can encourage the use of "sleeping" patents (Rivette and Kline, 2000; Palomeras, 2003). As noted earlier, these patents may not be of value, and hence have no demand. Alternatively, there could be transaction costs or other barriers to technology trade that prevent this potential market from being realized. Our analysis can shed light on this issue. By estimating the determinants of licensing given that the owner wants to license, we can find which factors encourage or discourage actual licensing. We can then understand the nature of these impediments, and how and whether they can be removed. Of course, markets for technology are unlikely to eliminate all the unused patents, but they can contribute in reducing them. As a matter of fact, some assessments have suggested that there was a notable untapped market for technology in Europe around the end of the 1990s (Arora et al., 2001).

To anticipate our key results we find that there is room for increasing the actual rate of technology licensing. We show that practically all the determinants of licensing proposed by the literature (protection, generality, value, etc.) affect the willingness to license. This suggests that the technology suppliers know the characteristics of the patents that are likely to be sold. By contrast, only a few of these characteristics affect the conditional probability of an actual license. For example, we found that proxies of the value of patents or their generality do not affect the conditional probability of licensing. If they did, the reasons why a licensable patent was not licensed could simply be that the patents were not valuable or general enough, and hence had limited demand. If instead, the suppliers select more valuable or general patents for licensing, the pool of licensable patents is less discriminatory along these characteristics. Simply put, if all the licensable patents are valuable or general, these factors cannot explain actual licensing. As a result, the determinants of the conditional probability of licensing are more subtle. The only extensive study that we know on this matter (Razgaitis, 2004) finds that the failure to conclude a licensing deal ranges from the inability to find potential licensees, to difficulties in getting internal approval, disagreements on conditions like geographical or exclusivity restrictions, and other such reasons. Divergence on licensing payments is one of these reasons, but it is not more important than the others. Since licensing contracts have exploded in recent years, many of these impediments may depend on a general inexperience with such contracts, and related lack of standardization in their format or other aspects. Policies aimed at removing these transaction costs may then expand the technology markets, and improve the rate of economic utilization of patents.

This paper is organized as follows. Section 2 presents the theoretical background and the hypothesis to be tested. Section 3 describes the data source and applied methodology. Section 4 reports the results from our analysis. Section 5 discusses the empirical results and concludes.

2 Theoretical background and hypotheses

The theoretical and empirical literature on technology licensing has developed several hypotheses about the factors that affect the decision to license proprietary knowledge, and patents in particular.

Strength of patent protection

Stronger patents can encourage technology licensing because they make it more difficult for the licensee to invent around the patent. More generally, since licensing implies lower control on the diffusion of the technology, the strength of patent protection makes it more difficult for anyone to free ride on the right to use or produce the technology. Arora (1995) developed a theoretical model showing that bundling tacit know-how with codified knowledge protected by a patent reduces problems of opportunism and make it possible to realize contracts for the exchange of technologies. In his model the licensee needs the tacit knowledge to use the technology productively. Stronger patent protection encourages the licensor to transfer an amount of know-how closer to the first best. In a similar vein, Gallini (2002) shows that stronger protection discourages the licensee to terminate the licensing contract or aggressively compete with the licensor on the technology market, which encourages licensing. In this case licensing can also mitigate the problem raised by Merges and Nelson (1990) and Scotchmer (1991) of discouraging further research aimed at developing potentially infringing subsequent inventions, especially when technologies are cumulative or science-based.

In the empirical literature there is evidence that stronger patents reduce transaction costs in technology licensing contracts and favour vertical specialization (Arora, 1996; Nakamura and Odagiri, 2003; Arora and Merges, 2004). Anand and Khanna (2000) show that in the chemical sector, and especially in pharmaceuticals and biotechnology, where patent protection is more effective, there is a higher propensity to license than in other industries. Gans, Hsu, and Stern (2002) find that the presence of patents in the technology portfolio of the new firms increases the likelihood that they licence their technologies to an incumbent firm instead of entering into the final market for product. By using the CMU survey of US companies (Cohen et al., 2000), Arora and Ceccagnoli (2006) find that the effectiveness of patent protection, as perceived by the surveyed R&D managers, positively affects the propensity to license when complementary assets are absent or unimportant.

Generality of the technology

More general technologies, i.e. with a wider spectrum of potential applications, are more likely to be licensed. First, a higher number of applications means greater potential demand for the technology as it may serve a larger number of uses. Second, this makes it more likely that some of the uses are distant from the applications of the patent holder, who may then be more inclined to license it because the licensee is in a fairly remote final market, and the potential competition is weaker. Moreover, from a theoretical perspective, Bresnahan and Gambardella (1998) developed a theoretical model in which more general-purpose technologies are associated with a greater vertical specialization in industry and the formation of upstream technology specialist firms which license the technology to several manufacturers in different industries.

Scientific nature of the technology

Teece (1986) suggested that the tacit or codified nature of knowledge can affect the licensing decision. Codified knowledge is easier to imitate, but it is also easier to transfer because it can be articulated more clearly. This is because a good deal of the knowledge required to use the technology can be summarized in written forms, or in algorithms or designs. Scientific knowledge is typically more codified, which makes the transfer of science-based technologies easier. By contrast, technologies that are largely based on tacit knowledge require much more than the blueprints to use them effectively (Arora and Gambardella, 1994). Since it is codified, scientific knowledge also makes it easier to protect the patent because it is clearer what the object of the protection is. Technologies based on tacit knowledge are instead subject to more ambiguities about what is protected. Both easier transfer and more effective protection then make patents that rely on scientific bases more likely to be licensed, while making technologies based on tacit sources less likely.

Economic value of the technology

Licensed patents have a higher economic value. Since the licensee buys the license at a price, he needs to obtain a discounted stream of rents from the patent higher than the price paid. Many patents are worth nothing. They produce a zero or even negative stream of profits if an attempt is made to exploit them economically. These patents, and particularly the patents in the left tail of the value distribution of patents, will then not meet any demand in the market. To put it more broadly, they are less likely to be licensed than those in the right tail. Clearly, not all valuable patents will be licensed. But a licensed patent is in any case picked from a subset of better patents. Moreover, valuable patents induce a higher demand. If there are more potential buyers, the supplier enjoys a higher bargaining power, which raises the price of the license. More generally, the seller can benefit from a higher share of the gains from trade, which encourages the sale of the patent.

To be sure, the foregoing argument assumes that information about the value of the patent is fairly transparent. If there is significant asymmetric information between the buyer and the seller a classical "lemon" problem may arise. The buyer knows that the sellers would only sell lemons, and therefore would only buy at low prices. In this case the market for patents would be small and populated by low value patents. However, it is unlikely that today's markets for patents are characterized by significant asymmetric information. The patents disclose a good deal of information, which is even more pronounced with the availability of on-line information and the ease with which patents can be searched for and retrieved. Moreover, the buyers in this market are technologically knowledgeable firms, often large ones. As a result, "lemon" problems are unlikely, and the licensed patents are on average economically valuable technologies. At any rate, our empirical analysis enables us to test whether licensed patents are more or less valuable, thereby assessing these competing views.

Firm size and complementary assets

The large firms are less likely to license their technologies. There are two related reasons. The first one has to do with size *per se*. Arora and Fosfuri (2003) develop a model showing that firms license a technology when the "revenue effect" deriving from the licensing fees is higher than the "rent dissipation effect" represented by the loss of firm profits due to the increased competition in the product market after licensing. Many factors influence either one of the two effects. For instance, other things being equal, stronger patent protection favours licensing because it makes it harder to imitate the innovation. This raises the revenue effect because the buyer can hardly reproduce the technology, and the seller is more confident that he can remain a monopolist in the technology market. Similarly, the rent dissipation is smaller if the licensee is in a distant market – e.g. because the technology is broad and the licensee is in a different final sector, or he is in a distant geographical market in which the licensor does not operate.

Arora and Fosfuri then show that if the licensor has a small market share, the rent dissipation effect is smaller because there is a lower loss from creating another competitor after licensing. To see this, consider the extreme case in which the licensor has no market share. In this case there is no rent dissipation because the licensee would not take any market share from the licensor. By contrast, if the licensor is a monopolist, there is no incentive to license. This is because the monopolist can only extract as much as the duopoly profits from the licensee, and the sum of the duopoly profits from the license (revenue effect) plus the duopoly profits obtained in the market after licensing is always lower than the monopoly profits that the firm earns without licensing. In general, they show that the larger the market share of the licensor the higher the loss in profits due to the creation of another competitor from the license. As a result, larger firms, which have higher market shares, license less because they have more to lose from licensing.

The second reason is that large firms are integrated, and typically own the complementary assets for innovation. Moreover, they can obtain capital more cheaply either because they have internal funds or because market power or other factors facilitate their access to the financial market. Thus, they can buy complementary assets quickly and more cheaply if necessary. This makes integration of the technology in their downstream business operations less costly. Teece (1986) provides an articulated discussion of the role of complementary assets in reducing the propensity to license. Arora and Ceccagnoli (2006) also discuss this point and they verify it empirically.

Conversely, the smaller firms, especially start-ups and younger firms in technology-based businesses, are more likely to license since they may miss co-specialised assets for innovation. For these reasons they may enter the market by supplying their technologies or by forming coalitions with established firms (Teece, 1986; Kollmer and Dowling, 2004). In addition, especially in recent years, the rise of technology markets has encouraged many smaller firms and start-ups to follow a licensing business model whereby they choose strategically not to become downstream producers, but focus on technology licensing without investing in the complementary assets. Examples include the so-called fab less or chip less companies in semiconductors, or the small research-intensive firms in the biotech industry. This suggests that once a small firm or a start-up lacks the complementary assets to innovate, in current markets and industry settings there are factors that encourage them to remain a specialized business licensing out rather than integrating technology.

The association between smaller firms and licensing has been emphasized by several streams of the literature. For example, in the organizational literature on entrepreneurship, Baron and Hannan (2002) or Meyer and Roberts (1986) argue that there are very different organizational blueprints inside the small and young firms. This suggests that the small firms that started from their very foundation with a strategic focus are more likely to grow and preserve this focus over time. Since the entrepreneur's mental schemes greatly affect these blueprints, the fact that the entrepreneur is also an inventor is a sign of the innovative characteristic of the venture, and positively affects the probability that the firm will remain a technology supplier. As a matter of fact, some authors have suggested that engineers and scientists prefer to work in small independent companies rather than larger companies (Freeman and Soete, 1997).

Moreover, licensing can be an optimal tool for the new small firms to increase their reputation by establishing links with consolidated companies (Teece, 1986; Stuart et al., 1999; Shane and Venkataraman, 2003). These links may occur when the new ventures spin-off from large firms which can be buyers of their technology. Arora and Merges (2004) put up a structured argument on this topic. They maintain that with strong intellectual property rights and positive information spilling over between a buyer and a supplier of technology, vertical specialisation is preferred to integration. Moreover, for the buyer firm it is more efficient to spin-off a specialized and motivated independent firm endowed with patents from which it can subsequently buy the technologies through supply contracts. In this way the independent firm can also learn from other buyers and leak some information to the original parent company. In line with Arora (1995, 1996) the independent licensee will also face fewer transaction costs for customising the technology to the user needs and to transfering know-how to their original employer, given the existence of established links and reputation reducing the risks of opportunism. Finally, evidence from Arora and Gambardella (1990) shows that large firms invest in minority shares of new companies in biotechnology not only to monitor external research, but also to establish preferential links with new firms for acquiring and commercialising important inventions. The recent literature on corporate venturing and corporate entrepreneurship further highlights these relationships between incumbents and new firms (e.g. Chesbrough, 2002).

Core vs. non-core technologies

Large companies are more likely to license their non-core technologies. The resource- and competence-based view of the firm has stressed that firms should base their sustainable competitive advantage on heterogeneous, imperfectly mobile, and inimitable resources, or more generally on resources protected by isolating mechanisms from imitation by the competitors (Rumelt, 1984; Barney, 1986; Peteraf, 1993). But even a large firm is unable to maintain highly competitive skills and capabilities in a wide range of domains. As a matter of fact, Prahalad and Hamel (1990) emphasized that firms should invest in a few core technologies.

However, the increasingly complex and multi-technology nature of products and processes have induced large firms to invest in a wide range of technologies necessary for integrating different components and subsystems (Patel and Pavitt, 1997; Granstrand et al. 1997), or for building the internal capability necessary for selecting and assimilating external knowledge (Cohen and Levinthal, 1989). This is confirmed by empirical evidence showing that large firms have a broader technological than product diversification (Gambardella and Torrisi, 1998; Giuri et al., 2004). Typically, it is in the peripheral technologies that firms do not master the downstream production and commercialisation assets. As a consequence, they are more likely to license fringe or peripheral rather than core technologies. Moreover, because they can more effectively exploit production and commercialization in the latter case, they have greater incentives to protect them strategically than for the non-core technologies. This reinforces the probability that core technologies will not be licensed (see also Rivette and Kline, 2000).

Competition

Other things being equal, if there are a few firms or institutions holding the "secrets" of the technology, licensing is less likely. This is because their monopolistic position enables them to extract higher rents from exploiting the technology. This is especially true when the technology holders are firms with downstream capabilities. By contrast, when there are many firms or institutions operating in a technological domain, licensing is more likely - the more so if there is a higher share of small firms or non-profit research centres with little or no downstream capabilities. Similarly, if there are many agents holding the technology it is harder to prevent any one of them from licensing through agreements of various sorts. Then, if any of them licenses, and the technology secrets diffuse, the others have an incentive to license as well because the secret can no longer be kept, and the firms can make at least some rents in the technology market (see Arora and Fosfuri, 2003).

A similar argument can be made for competition in the downstream market. As discussed earlier, Arora and Fosfuri (2003) argued that larger market shares reduce the incentive to license. They also show that with more competitors in the product market, the entry of an additional competitor has a smaller effect on incumbent profits than if there were fewer rivals – i.e. the competitive profits with N rivals are closer to the competitive profits with N+1 rivals (viz including the licensee) if N is larger. In other words, if the market is already competitive, having one more competitor does not affect the rent dissipation effect considerably. By contrast, with few rivals the addition of a new competitor may have a sizable effect on the current profits of the licensor. As noted earlier, in the extreme case in which the potential licensor is a monopolist in the product market, he will have no incentives to license.

Other references

Other studies in the literature have discussed the determinants of technology license. To our knowledge they typically reiterate, though possibly with different arguments, the hypotheses discussed so far. Some of them bring together different factors among those discussed earlier. For example, the literature has pointed out that patent breadth and strength have an additional impact on technology licensing when technology is cumulative. As a matter of fact, not only broad patents make licensing feasible and more efficient, but licensing becomes necessary if second-generation products are to be developed by other firms that would otherwise infringe the broad patent (Scotchmer, 1991). This is especially true when the patented innovation is the output of basic science. With pioneer patents including general and basic knowledge with many potential second generation applications, the first innovator may miss the knowledge and complementary assets in all possible applications, therefore licensing becomes a valuable option. Specifically, Scotchmer (1991) maintains that when the innovation is cumulative, it is difficult to create the incentives for producing broad first-generation innovations if the first innovator cannot also appropriate part of the returns from the second generation of innovations. However, when the licensing fees are large enough to provide sufficient incentive to the first innovator, they may not provide enough incentive for second-generation innovations. She concludes that prior agreements among innovators at different stages of the innovation process may mitigate this problem. In Green and Scotchmer (1995), licensing by the first innovator before the second innovators commit to R&D investments can also provide incentives to the innovators.

3 Data and Variables

3.1 The PatVal-EU Dataset

Since this paper is about the determinants of technology licensing by the for-profit firms, we only used the PatVal sample of firm patents, viz 8207 of the 9017 PatVal patents. We excluded the patents assigned to universities and other non-profit research centres (government research labs, hospital, foundations, etc.). We included patents assigned to individuals because they are in large part for-profit micro-firms or professional studies. However, they constitute only 2.5% of firm-patents.

Missing values for some variables in our regressions reduced the final sample that we used in our probit regressions in Section 4.1 to 7105. Unfortunately, for the Dutch inventors PatVal did not record information about willingness to license patents that were not eventually licensed. Thus, for our Heckman probit analysis in Section 4.2 we employed only 6156 observations, i.e. the 7105 observations without the Dutch inventor patents. By comparison, we also run the simple probit equations in Section 4.2 only for the latter 6156 observations. The results were not different from those obtained using 7105 observations.

Table 1 lists all the variables used in our analyses. Table 2 provides descriptive statistics for the 7105 observations.

Table 1. Definition of variables

Variable name	Definition
Dependent variables	
LICENSE	Dichotomous variable equal to 1 if the patent was licensed and 0 if not licensed
WILL_LICENSE	Dichotomous variable equal to 1 if the owner was willing to license his patent (whether licensed or not) and 0 if not
Covariates and controls	
NIPC4	Number of 4-digit IPC technological classes in which the patent has been classified by the EPO examiners
SC_LIT	Importance of the scientific literature as a source of knowledge for the research that led to the patented innovation (0-5 Likert scale: 0 not important, 5 = very important)
SCIENCE_LABS	Maximum score of importance attributed to university or non-university public labs as sources of knowledge for the patent (0-5 Likert scale).
TACIT	Sum of the 0-5 scores attributed to three sources of knowledge for the patent: users, suppliers and competitors
LARGEFIRM	Dummy equal to 1 if the inventor (PatVal respondent) was employed in a firm with more than 250 employees
MEDIUMFIRM	Dummy equal to 1 if the inventor was employed in a firm with 100-250 employees
SMALLFIRM	Dummy equal to 1 if the inventor was employed in a firm with less than 100 employees
MARGINAL	Dummy equal to 1 if the patent is marginal or niche, and LARGEFIRM=1
BACKGROUND	Dummy equal to 1 if the patent is background, and LARGEFIRM=1
TARGET	Dummy equal to 1 if the PatVal respondent indicated that the invention was the targeted achievement of a structured R&D project, and equal to 0 if not (e.g. by-product of other activities, pure outcome of creativity and inspiration)
CLAIMS_GRANT	Number of claims listed in the patent at the date of grant
OPPOSITION	Dummy equal to 1 if the patent was opposed at the EPO after the grant
OBS_III_PARTY	Dummy equal to 1 if third parties have presented observations at the EPO prior to the grant of the patent
STATES	Number of designated countries in which the patent was applied for by the applicant
IPC4_C4	Share of the patents held by the top four applicants in each 4-digit IPC patent class (computed by using the entire sample of EPO-Epasis patents in 1993-1997 of inventors located in the six surveyed countries)
IPC4_D10	Dummy equal to 1 if there are ten or fewer patents in the 4-digit IPC patent class
DE, ES, FR, IT, NL, UK	Dummies for the six countries (Germany, Spain, France, Italy, the Netherlands, UK) where the first inventor of the PatVal patent is located.
AppYear	Six dummies for application years 1993-1998
TechClass	Thirty dummies for the technological classes of the patent (ISI-INIPI-OST classification). The list is reported in the Appendix.
Macro_TechClass	Five dummies for the macro technological classes (ISI-INIPI-OST classification): Electrical Engineering, Instruments, Chemicals & Pharmaceuticals, Process Engineering, Mechanical Engineering.

Table 2. Descriptive statistics

	Mean	St. Dev.	min	Max	N
Dependent variables					
LICENSE [a]	0.114	0.318	0	1	7105
WILL_LICENSE	0.187	0.390	0	1	6156
Covariates and controls					
NIPC4 [b]	1.430	0.690	1	7	7105
SC_LIT [b]	2.504	1.870	0	5	7105
SCIENCE_LABS [b]	1.205	1.636	0	5	7105
TACIT [b]	6.766	4.106	0	15	7105
LARGEFIRM	0.761	0.427	0	1	7105
MEDIUMFIRM	0.096	0.294	0	1	7105
SMALLFIRM	0.143	0.351	0	1	7105
MARGINAL	0.031	0.172	0	1	7105
BACKGROUND	0.061	0.240	0	1	7105
TARGET	0.364	0.481	0	1	7105
CLAIMS_GRANT [b]	10.642	6.902	1	131	7105
OPPOSITION	0.102	0.302	0	1	7105
OBS_III_PARTY	0.006	0.075	0	1	7105
STATES [b]	8.585	4.729	1	19	7105
IPC4_C4 [b]	0.336	0.173	0	1	7105
IPC4_D10	0.009	0.094	0	1	7105
DE	0.427	0.495	0	1	7105
ES	0.031	0.174	0	1	7105
FR	0.065	0.247	0	1	7105
IT	0.160	0.367	0	1	7105
NL	0.134	0.340	0	1	7105
UK	0.182	0.386	0	1	7105
AppYear1993	0.028	0.166	0	1	7105
AppYear1994	0.282	0.450	0	1	7105
AppYear1995	0.265	0.441	0	1	7105
AppYear1996	0.231	0.421	0	1	7105
AppYear1997	0.150	0.357	0	1	7105
AppYear1998	0.045	0.207	0	1	7105

[a] in the sample of 6156 observations the mean of licensing is 0.111. [b] Absolute value, not in logs.

Below we describe our dependent and independent variables. The sources are PatVal, and the EPO-Epasis dataset which is used for additional data about the patents (for additional information about the EPO patent indicators see Harhoff et al., 2005 and Webb et al., 2005). We also use the Who Owns Whom dataset to group firms under the names of their parents.

3.2 Dependent Variables

Each respondent in PatVal was asked whether the patented innovation was licensed by the patent holder to an independent party. When the patent was not licensed, the respondent was also asked whether he thought that the patent holder was willing to license it. We used this information to create two dependent variables:

LICENSE: This is a dichotomous variable equal to 1 if the patent was licensed and 0 if not. This is the dependent variable of our probit estimation in Section 4.1. From Table 2, the mean value of LICENSE is 11.4%, which is the share of licensed patents in our sample (11.1% for the 6156 observations).

WILL_LICENSE: This variable takes the value 0 if the owner was not willing to license his patent, and 1 if he was willing to license (whether actual or not). This is the dependent variable of the selection equation of the Heckman estimation in Section 4.2, where LICENSE is the dependent variable of the selected equation. The sample average of WILL_LICENSE is 18.7% (6156 observations).

3.3 Covariates and Controls

Strength of patent protection and generality

Measuring patent protection is not straightforward. The extent of patent protection depends on the policy of the patent system of a country. For example, patents are stronger if they are well enforced by the judicial system. However, we would not get very far by measuring patent protection in this way because all our observations would be part of the same patent system. Moreover, differences across individual countries would be too coarse for our data, and would mix with other country-level fixed effects.

Most of the literature discussed in the earlier Section measures patent protection at the patent level by the scope or the length of patent protection. Again, we cannot use the latter because it is common to all the patents. The breadth of patent protection can instead vary across them. Following the literature, the broader the scope of protection of the patent, the larger the number of domains or applications covered by it, and the lower is the opportunity of another party to invent around the patent.

At the empirical level the most commonly used proxies for patent breadth are the number of claims and the number of IPC technological classes listed in the patent. We retrieved both measures from the EPO-Epasis dataset.

CLAIMS_GRANT: Lerner (1994) notes that the best way to measure patent scope would be a direct assessment of the breadth of patent claims, which is a practice often undertaken by firms before concluding a transaction such as an acquisition or a licensing agreement. However, assessing the breadth of all patents' claims is an impractical exercise in an empirical analysis with a large number of observations. As a proxy for patent scope we thus used the number of claims listed in a patent. In so doing, we exploit the possibility that different technologies may have different characteristics that make them easier or harder to protect, e.g. their degree of codification, or the fact that there are other patents in the nearby domain that limit its scope. Thus, a larger number of claims may mean that the field is more open or that the technology can make more allegations of protection. To avoid endogeneity we employ the number of claims at the moment of grant, not application. Before the grant, the patent examiners revise the claims made by the applicant. The claims at grant are then checked by an independent party.[1] A more serious problem is that it is not clear whether the number of claims measures protection rather than the value of the patent (e.g. Lanjouw and Schankerman, 2004). In our empirical analysis, we will thus interpret this variable cautiously.

NIPC4: Another proxy for patent scope is the number of 4-digit IPC technological classes in which the patent has been classified by the EPO examiners. Lerner (1994) also used this measure as a proxy for patent scope. The number of IPC classes can also be interpreted as a measure of the generality of knowledge. Thus, like with the claims we cannot unambiguously interpret this variable as a measure of patent scope (hence protection) or of the generality of the technology. Because theoretically the two concepts have the same impact on licensing, we can assess empirically whether either of them matters.

Scientific nature of the technology

As proxies for the scientific nature of the knowledge underlying the invention, we use the following set of variables:

SC_LIT: Each PatVal respondent was asked to rank on a 0-5 Likert scale the importance of the scientific literature as a source of knowledge for the research that led to the patented innovation.

SCIENCE_LABS: The respondents were also asked to rate on the same 0-5 scale the importance of university or other public research labs as sources of knowledge for the patent. We defined this variable as the maximum score attributed to university or non-university public labs.

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[1] For 60% of the patents in our sample the claims at grant are equal to the claims at the moment of the application. On average the patents at grant have 0.91 fewer claims (slightly less than 10% given the average of CLAIMS_GRANT in Table 2). Thus, the examiners do not change things dramatically. This may be explained by the fact that especially in recent years the notable increase in the number of applications is making more and more demands on the examiners' time. At any rate, in our empirical analysis we try our regressions without introducing the claims variable, and the results do not change.

TACIT: This is the sum of the 0-5 scores in PatVal attributed to three sources of knowledge: users, suppliers, competitors. These are more tacit sources of knowledge, especially when compared to scientific sources.

Economic value of the technology

We employ three measures of the economic value of the technology, from EPO-Epasis.

OPPOSITION: This is a dummy equal to 1 if the patent was opposed at the EPO after the grant. Any third party may file an opposition at the EPO up to 9 months after the grant of a patent in order to challenge the validity of the patent in all designated countries. It is a measure of value because it is likely that a competitor of the applicant or another interested third party, who decide to file the opposition procedure, can be potentially damaged by the patent. Moreover, the opponent has to pay a fee for filing an opposition. Harhoff and Reitzig (2004) have shown that opposed patents are more likely to be correlated with other measures of economic value of the patent, such as forward citations, claims or designated countries.

OBS_III_PARTY: This is a dummy equal to 1 if third parties have presented observations to the EPO prior to the grant of the patent. According to the European Patent Convention (art. 115) any person may present observations concerning the patentability of the invention in respect of which an application has been filed. It is a measure of value because it is a sign of external consideration for the patent, for example by potential buyers or competitors.

STATES: This is the number of designated countries in which the patent was applied for by the applicant. It is a measure of the economic value of the technology because patenting in each new country entails an additional fee. Since the cost is incurred at the moment of the grant it can be thought of as a lower bound of the expected discounted stream of rents produced by the patent. It is clearly a noisy measure of value. For example, it is a measure of the value of the patent for the applicant, not for the potential buyers. If a given patent is granted to a firm with no stakes in foreign countries, it may not pay the corresponding fees, while an international company would. However, it is likely to be correlated with valuable technologies. Moreover, Lanjouw and Schankerman (2004) show that it is correlated with other measures of patent quality or protection.

Another commonly employed measure for the value of patents is the number of forward citations. In our analysis however this measure is likely to be endogenous. The PatVal patents had priority dates 1993-1998. Both citations and the decision to license occur later, and they may be affected by common shocks that we do not observe. Moreover, citations may occur because of licensing, for example they may be put by the licensee in their subsequent patents. Evidence on this is scattered. The only available evidence for university licensing shows that on average 16% of citations of licensed patents are made by licensees (Sampat and Ziedonis, 2003).

By contrast, the measures that we used are all defined at the moment of application or grant, thus before the occurrence of a licensing event. Moreover, opposition and observations by third parties are not decided by the licensor but by a third party. It is still possible that both the decision to license and the measures that we used are influenced by unobserved factors at the time of application or grant. We are aware of this possibility and we used these variables cautiously by gradually introducing them in our regressions. The various experiments produce very similar results.

Firm size and complementary assets

We lump firm size and complementary assets together in the same dummy variables for large, medium, and small firms. It is not easy to find specific measures of complementary assets for all the firms in a sample as large as ours. Moreover, because PatVal spans a wide spectrum of firm sizes, the variations across our size classes in the extent of complementary assets are large compared to variations within the same class.

LARGEFIRM: Dummy equal to 1 if the PatVal respondent indicated that he was employed in a firm with more than 250 employees (76.1% of the patents);

MEDIUMFIRM: Dummy equal to 1 if the PatVal respondent indicated that he was employed in a firm with 100-250 employees (9.6%);

SMALLFIRM: Dummy equal to 1 if the PatVal respondent indicated that he was employed in a firm with less than 100 employees (14.3%).

Core vs. non-core technologies

We also controlled for whether in the large firms the patented innovation is a core or non-core technology. This distinction is not meaningful for the small and medium firms because they own relatively few patents, which are presumably all core technologies. To create our measures of core and non-core technologies we used all the EPO patents (not just the PatVal ones) of inventors located in France, Germany, Italy, the Netherlands, Spain and the UK in the surveyed period (1993-1997). Each patent of our large firms was assigned to one of 30 technological classes. These classes are described later in this Section, as we also use them as dummies for control. Granstrand, Patel and Pavitt (1997) define the criteria to distinguish the technologies of a firm in four categories: core, background, marginal, and niche. We mimic their classification by using the share of each of the 30 technological fields on the total patents of the firm (patent share), and an index of the firm's revealed technology advantage in each of the 30 technological fields (RTA). The first one reflects the relative importance of each field in the firm's total technological portfolio. Since the average share is about 3%, this value is used to distinguish between above and below average shares. The RTA reflects the relative importance of the firm in each field of technological competence. This is defined as the firm's shares in total patenting in each of the 30 technological fields divided by the firm's share of total patenting in all the fields. RTA=2 distinguishes high from low RTA. We define:

- Core: dummy equal to 1 if patent share >3% and RTA>2
- Background: dummy equal to 1 if patent share >3% and RTA<2
- Marginal: dummy equal to 1 if patent share <3% and RTA<2
- Niche: dummy equal to 1 if patent share <3% and RTA>2.

Background technologies are, for instance, technologies of important components of the firm, or in complementary fields. The firm produces many of them because they are useful internally, but it is not a specialist compared to others in the area. By contrast, marginal technologies are relatively few and the firm is not specialised in them. The niche are like the marginal, but the firm is specialized in the area. In our sample, 87.9% of the patents of the large firms are core, 8.1% are background, 3.8% are marginal, and 0.2% are niche. To confirm that it makes little sense to distinguish among these classes for small and medium firms, their share of core patents are respectively 98.7% and 98.4%. We combine marginal and niche in one dummy, and construct the following variables:

MARGINAL: Dummy equal to 1 if the patent is marginal or niche, and the firm is a large firm (LARGEFIRM=1).

BACKGROUND: Dummy equal to 1 if the patent is background and the firm is a large firm (LARGEFIRM=1).

Competition

As noted earlier, technological or product competition raises the incentive to license. Unfortunately, it is hard to develop measures of product competition for all patents in our sample. This would require us to identify which product markets correspond to a certain patent area or technology and find the competitive structure of that market, a task which would be impractical with such a large number of firms and observations. We used the following variables:

C4_IPC4: This is the share of the patents held by the top four applicants in each 4-digit IPC patent class computed by using the entire sample of EPO-Epasis patents of inventors located in the six surveyed countries between 1993 and 1997.

IPC4_D10: This is a dummy variable taking the value 1 if there are ten or fewer patents in the 4-digit patent class, and zero otherwise. This dummy singles out cases in which the small number of patents in the class may make the concentration index not very meaningful.

As alternatives to C4_IPC4 we employed the one- and eight-applicant concentration index (and relative dummies), with no appreciable change in results. All these variables account for technological rather than product competition. As noted in the earlier Section, technological competition is one of the dimensions that we want to capture. Moreover, it is correlated with product competition, and as noted above it is easier to construct in our context. Our earlier discussion also pointed out that the effects of a competitive situation on licensing is more marked if the technology holders are smaller firms or universities with fewer stakes in the downstream activities, which then have a higher propensity to license. We then also used the share of licensing by university and non-profit research centres in the 4-digit IPC class, or the share of small firm licensing. These variables did not work as well as the concentration indices. One reason is that the licensing shares of university or non-profit research centres and of the small firms are very small, and they are zero for many technological classes.

Controls

TARGET: This is a dummy equal to 1 if the PatVal respondent indicated that the invention was the targeted achievement of a structured R&D project, and equal to 0 if not (e.g. by-product of other activities, pure outcome of creativity and inspiration). We expect this variable to be negatively correlated with licensing because a structured R&D project is more likely to be the outcome of a planned decision in a relatively hierarchical organization. In turn, this is correlated with firm size, the ownership of complementary downstream assets, and other factors that make it more likely to pursue the project internally. By comparison, by-products of other activities, outputs of creative jobs, and the like are more likely to be produced by smaller entities, less hierarchical organizations, and other factors associated with licensing.

TECHCLASS: Thirty dummies for the technological classes of the patent. We employed the technology-oriented classification system jointly elaborated by the German Fraunhofer Institute of Systems and Innovation Research (ISI), the French patent office (INPI) and the Observatoire des Science and des Techniques (OST). It distinguishes among 30 different fields of technology and five higher-level technology areas ("macro" technological classes) based on the International Patent Classification (IPC). For a direct comparison between the ISI-INIPI-OST technological classes and EPO IPC classes see Hinze et al. (1997). Breschi et al. (1998) provide an application and a detailed discussion of this classification. We find this classification to be particularly useful because it associates the 4-digit IPC classes, which are highly technological, to industrial sectors, or at least to classes that are much more intuitively associated with industries. The descriptive statistics for the 30 ISI-INIPI-OST technological classes are reported in Table A1 of the Appendix.

MACRO_TECHCLASS: Five dummies for the macro technological classes of the ISI-INIPI-OST classification above. They are: Electrical Engineering, Instruments, Chemicals & Pharmaceuticals, Process Engineering, and Mechanical Engineering.

DE, ES, FR, IT, NL, UK: Dummies for the six countries (Germany, Spain, France, Italy, the Netherlands, UK) where the first inventor of the PatVal patent is located. In our regressions we use DE as the baseline dummy.

APPYEAR: Six dummies for application years 1993-1998.[2]

We tried other variables as controls in our regressions, like the number of inventors in the patent (from EPO-Epasis), the sources of funds for the invention (from PatVal), or else. They do not add much to the results.

4 Empirical Results

4.1 Determinants of Licensing

We start by estimating a probit equation for the probability of licensing using our full sample of 7105 PatVal patents applied by firms. The structure of these models is well known. There is a latent variable $\mathbf{y} = \mathbf{X'}\boldsymbol{\beta} + \mathbf{e}$, where $\mathbf{X'}$ is an *n x k* vector of the *k* covariates and *n* observations, $\boldsymbol{\beta}$ is the *k x 1* vector of parameters to be estimated, and $\mathbf{e}$ is the *n x 1* vector of *i.i.d.* normally distributed errors. Since the latent variable is not observed, we estimate the probability of licensing *Prob*(LICENSE=1) $\equiv \Phi(\varepsilon_i < \boldsymbol{x}_i' \boldsymbol{\beta})$ where ε_i is the i^{th} observation of $\mathbf{e}$, $\boldsymbol{x}_i'$ is the i^{th} row of $\mathbf{X'}$, Φ is the standard normal, and the vector $\boldsymbol{\beta}$ is normalized by the standard error of $\mathbf{e}$.

[2] The PatVal survey originally targeted patents with priority date 1993-1997. However, a few 1998 patents sneaked in, and we controlled for them as well.

The empirical results in Table 3 report the marginal effects of changes in the covariates on the probability of licensing evaluated at the mean of the covariates, i.e. for the j^{th} covariate x_j they are $\frac{\partial \Phi(\boldsymbol{x}_i'\hat{\boldsymbol{\beta}})}{\partial x_j} = \beta_j \cdot \phi(\boldsymbol{x}_i'\hat{\boldsymbol{\beta}})$, where $\hat{\beta}_j$ and $\hat{\boldsymbol{\beta}}$ are the estimated parameters, $\boldsymbol{x}_i'$ is evaluated at the sample mean, and ϕ is the standard normal density. We report the marginal effects because they have a more direct interpretation (change in probability) than the parameters $\boldsymbol{\beta}$. The changes for the dummies go from 0 to 1. For the continuous variables STATA approximates the change in the probability of licensing produced by an infinitesimal change in the covariates defined consistently with the scale of the data. The way to understand this is that if we multiply the marginal effects in Table 3 by any change in the covariate we obtain the corresponding linear change in the probability of licensing. For all the covariates that are not dummies we used logs as indicated in the Table. Thus, we are measuring the changes in probability produced by a percentage change in the original variable.

We show the results of three estimations where we gradually introduce CLAIMS_GRANT and the proxies for the value of the patent. This is to show that the results do not change when we exclude these variables. For this and other reasons discussed in the previous Section, we do not think that the endogeneity of these variables is a serious problem in our study. In our discussion below we then always refer to the third column of Table 3. Finally, since there are firms holding several patents in our sample, we run all three regressions after clustering on firms. This takes into account any unobserved correlation among the errors of the patents belonging to the same company.

Table 3 shows that the most important effect on the probability of licensing is by far the size of the firm. Belonging to a large firm reduces the probability of licensing by 14.4 percentage points. The effect is statistically quite significant. It is also consistent with the basic statistics of our sample. While the unconditional share of licensing in our 7105 patents is 11.4%, the share of licensing of the large firms is 9.0%; for the small firms it rises to 25.3%. The most notable point of Table 3 is that other effects are statistically significant, but none of them is as sizable as the firm size class. For example, the three variables measuring the economic value of the technology are largely significant and their sign is the expected one. But a 50% increase in the number of countries in which the patent is applied (STATES) corresponds to just a 1.4% change in the probability of licensing, one-tenth of the effect of the firm size class. A 50% increase in STATES from its average is quite a reasonable change in our sample. From Table 2 the sample average of STATES is 8.6 and a 50% increase is just slightly smaller than a one standard deviation change (4.7 in Table 2). Similarly, an opposed patent, or one for which there is a third party observation, increases the probability of licensing respectively by 3.8% and 8.9%. The latter is closer to the large firm effect, but still more than 5% lower. The effect of CLAIMS_GRANT is again significant, but quite small. In Table 2, a one standard deviation increase from the sample average of CLAIMS_GRANT corresponds to about 65%, which translates into a 0.9% change in the probability of licenses. The distribution of claims is greatly skewed. There are a few hundred patents in our sample with 20 or more claims which correspond to a 100% increase or more with respect to the sample average of this covariate. Even a 50 claims patent (roughly 400% from the sample average), which is well into the first percentile of the claims distribution, would increase the probability of licensing only by slightly more than 5%.

There are other significant effects. The SCIENCE_LABS covariate is significant. Thus, more scientific patents are more likely to be licensed. Similarly, more general patents (NIPC4), and technological areas with a larger number of technology producers (smaller C4_IPC4) are associated with greater probabilities of licensing. The MARGINAL technologies are also more likely to be licensed, while the effect is less pronounced for BACKGROUND technologies. In the latter case the large companies probably still have some strategic interest to keep them inside because they can be important for their core products. The marginal technologies instead entail a potentially good revenue effect and a small rent dissipation effect, given that the firms focus on other businesses (e.g. Rivette and Kline, 2000). In all these covariates a one standard deviation change from the sample mean is in the order of a 50% increase (see Table 2). The reader can check this from our estimates in Table 3. Fifty percent increases in these covariates entail relatively small changes in the probability of licensing compared to LARGEFIRM.

To summarize, the empirical analysis of this Section shows that the previous theories of the determinants of licensing are broadly consistent with our data. We find that measures of patent protection, the generality of knowledge, the value of the patent, the science-based nature of the technology, competition, and firm size or complementary assets have a positive effect on the probability of licensing. However, the firm size or complementary asset effect dwarfs all the others. A large firm has a probability of licensing that is orders of magnitude smaller than the small firms.

Table 3. Probit estimations of the determinants of actual licensing, marginal effects

Variable	Probit Lic1	Probit Lic2	Probit Lic3
log(NIPC4)	0.024	0.023	0.022
	(0.007)***	(0.012)**	(0.015)**
log(1+SC_LIT)	-0.003	-0.003	-0.004
	(0.655)	(0.612)	(0.536)
log(1+SCIENCE_LABS)	0.029	0.028	0.027
	(0.000)***	(0.000)***	(0.000)***
log(1+TACIT)	-0.001	0.000	-0.001
	(0.912)	(0.946)	(0.841)
LARGEFIRM	-0.144	-0.142	-0.136
	(0.000)***	(0.000)***	(0.000)***
MEDIUMFIRM	-0.078	-0.078	-0.077
	(0.000)***	(0.000)***	(0.000)***
MARGINAL	0.060	0.062	0.066
	(0.103)	(0.087)*	(0.078)*
BACKGROUND	0.017	0.018	0.021
	(0.316)	(0.299)	(0.217)
TARGET	-0.001	-0.001	-0.001
	(0.911)	(0.877)	(0.864)
log(IPC4_C4)	-0.064	-0.063	-0.050
	(0.087)*	(0.092)*	(0.186)
IPC4_D10	0.053	0.055	0.064
	(0.253)	(0.237)	(0.193)
ES	0.027	0.034	0.030
	(0.311)	(0.223)	(0.262)
FR	0.021	0.018	0.013
	(0.248)	(0.318)	(0.443)
IT	0.001	0.000	-0.002
	(0.969)	(0.987)	(0.856)
NL	0.028	0.027	0.024
	(0.055)*	(0.073)*	(0.133)
UK	0.025	0.019	0.018
	(0.053)*	(0.134)	(0.158)
log(CLAIMS_GRANT)		0.016	0.013
		(0.031)**	(0.057)*
OPPOSITION			0.038
			(0.011)**
OBS_III_PARTY			0.088
			(0.163)
log(STATES)			0.027
			(0.000)***
AppYear Dummies	Yes	Yes	Yes
TechClass Dummies	Yes	Yes	Yes
N	7105	7105	7105
Ll	-2362.429	-2358.930	-2343.408
chi2	343.780	364.800	385.980
Predicted prob.	0.102	0.101	0.100

* p<0.10, **p<0.05, ***p<0.01. p-values in parenthesis, based on robust standard errors adjusted for clusters by firms' identifier.

4.2 Actual vs. Potential Licensing

The Heckman Selection probit

We then estimated a model in which the applicants first decide whether or not to license a patent, and if so whether the patent is actually licensed. We employ a Heckman selection probit model. This is a maximum likelihood model in which not only the selection equation but also the "selected" equation is a probit model.

Specifically, there are two latent variable models $\mathbf{y_1} = \mathbf{X}_1' \boldsymbol{\beta}_1 + \mathbf{e_1}$ and $\mathbf{y_2} = \mathbf{X}_2' \boldsymbol{\beta}_2 + \mathbf{e_2}$. The $\mathbf{X'}$s are $n \times k_i$ vectors of the k_i (i=1,2) covariates and n observations in the two equations, $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are the $k \times 1$ vectors of parameters to be estimated, and $\mathbf{e_1}$ and $\mathbf{e_2}$ are the $n \times 1$ vectors of *i.i.d.* normally distributed errors where $\mathbf{E}\,\mathbf{e_1}\mathbf{e_2'}$ is a non-diagonal matrix. Since the latent variables are not observed, we estimate a probability model whose log-likelihood function is

$$\log L = \sum_{\substack{LICENSE=1,\\ WILL\_LICENSE=1}} \log \Phi\left(\varepsilon_1 > -x_1'\beta_1, \varepsilon_2 > -x_2'\beta_2\right) \;+$$

$$\sum_{\substack{LICENSE=0,\\ WILL\_LICENSE=1}} \log \Phi\left(\varepsilon_1 < -x_1'\beta_1, \varepsilon_2 > -x_2'\beta_2\right) \;+ \sum_{WILL\_LICENSE=0} \log \Phi_2\left(\varepsilon_2 < -x_2'\beta_2\right)$$

where ε_1 and ε_2 are the two generic elements of $\mathbf{e_1}$ and $\mathbf{e_2}$, $\boldsymbol{x}_1'$ and $\boldsymbol{x}_2'$ are the corresponding row vectors of the k_i covariates of the two equations (i=1, 2), $\Phi(\cdot)$ is a bivariate standard normal, $\Phi_2(\cdot)$ is the standard marginal normal of ε_2, and the three summations correspond to the following three probabilities (and related sets of observations):

1) *Prob*(LICENSE=1, WILL_LICENSE=1);
2) *Prob*(*LICENSE*=1, WILL_LICENSE=0);
3) *Prob*(WILL_LICENSE=0).

The latter is a marginal probability because when WILL_LICENSE=0, LICENSE=0 with probability 1. We estimate $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, and the covariance between ε_1 and ε_2, through maximum likelihood. In all our estimations we cluster observations by firms to take into account potential unobserved correlations among the patents owned by the same company.

Identification

In this model we need to identify the selection equation. This is not easy because in principle we cannot rationally exclude any variable from the selected equation. This is also in the very nature of our test. For example, our science or tacitness variables can affect the willingness to license because the supplier knows that they affect transaction costs or protection. But they can also influence the conditional probability of licensing because if a non-codified technology is offered for licensing, the buyers are less likely to buy it, or more ambiguities will be raised before or during the negotiations which reduce the probability of concluding the deal. Similarly, our variables for generality and value can in principle affect both the probability of selection and the conditional probability of licensing. A more general or a more valuable technology is more likely to be offered for licensing because the suppliers expect more buyers to be interested in them, with potentially higher revenue from licensing. At the same time, if less valuable or less general technologies are offered, fewer buyers will be interested in them reducing the conditional probability of licensing. The competition variable, C4_IPC4, together with its dummy IPC4_D10, is another potential exclusion restriction. As noted in Section 2, when there are many potential technology suppliers, each of them is less concerned about restricting the diffusion of the technology because it is harder to do it in any case. This ought to influence the decision of the suppliers to supply, not the decision of the buyers to buy. However, with many potential licensors in a technological area it may be harder to find a buyer for each license because of the greater supply and competition.

The variables that affect protection, CLAIMS_GRANT or NIPC4, or the non-core technologies, MARGINAL or BACKGROUND, could in principle affect the decision to license but not the actual licensing. If a technology can be protected, the supplier can choose to license it for the reasons that we discussed. Yet, this should not affect whether the buyer wants to buy it or not. Perhaps the supplier exercises more effort to sell licenses that are better protected, but this cannot be a first-order effect. Similarly, if a technology is non-core for the licensor, this should not affect the buying decision. The reason why we did not use these variables as exclusion restrictions is that we cannot be sure that they are just measures of protection or of non-core technologies. As noted, CLAIMS_GRANT can be a measure of the value of the patent, and NIPC4 can be a measure of generality. The non-core variables could be a measure of value, as they are technologies in which the firm may have less expertise.

We concluded that the only variables that can be safely excluded from $\boldsymbol{x}_1'$ but not from $\boldsymbol{x}_2'$ are the 30 technological dummies. The rationale is that they account for differences across sectors, which in turn account for differences in the nature of the technology, competition, and related factors. But we already have quite a few covariates spanning potential differences across sectors or technologies. Moreover, in our regression of the actual licensing decision we included the 5 macro-technological class dummies. In addition, we performed several robustness checks. First, we tried the same Heckman probit model using as exclusion restrictions some of the variables that have an insignificant impact in the selected equation when using the 30 technological dummies as exclusion restrictions. The results are very stable. As we shall see, we also find an insignificant correlation between the two equations, suggesting that we can estimate the two probits independently. As a matter of fact, we estimated the independent licensing equation only for the sample of patents that are offered for licensing, and with the 30 technological dummies instead of the 5 macro-technological classes. Again the results do not change.

Empirical Results

We present our empirical findings in Table 4. As in the previous Section, we report the marginal effects rather than the **β**s because they have a more direct interpretation. We show the impacts of our covariates on three probabilities:

1) The probability of selection, *Prob*(WILL_LICENSE=1);

2) The probability of licensing conditional on selection, *Prob*(LICENSE=1|WILL_LICENSE=1);

3) The marginal probability of licensing, *Prob*(LICENSE=1, WILL_LICENSE=1).

As in the previous Section, Table 4 reports the effects of changes from 0 to 1 in the dummy variables, while for the continuous variables it approximates the effects of appropriately scaled unit changes in the covariates. Since our continuous covariates are in logs, the marginal effects in Table 4 can be multiplied by any percentage change to obtain the corresponding effects on the probability. We performed the same sets of regressions of the previous Section, i.e. we experimented with and without claims or the proxies for patent value on the ground that they may be endogenous. The results are very similar. Here we present the estimates using all the covariates. We also found that the correlation between the two probit equations is not significantly different from zero. As noted, independent estimation of the selection equation and of the licensing equation for the selected sample produced similar results.

Table 4. Heckman Probit estimations of actual licensing and willingness to license, marginal effects

Variable	P-selection	P-conditional	P-bivariate 11
log(NIPC4)	0.032	0.008	0.021
	(0.018)**	(0.832)	(0.038)**
log(1+SC_LIT)	0.009	-0.057	-0.004
	(0.372)	(0.030)**	(0.584)
log(1+SCIENCE_LABS)	0.045	-0.014	0.026
	(0.000)***	(0.588)	(0.000)***
log(1+TACIT)	-0.011	0.023	-0.003
	(0.121)	(0.283)	(0.562)
LARGEFIRM	-0.190	-0.150	-0.158
	(0.000)***	(0.000)***	(0.000)***
MEDIUMFIRM	-0.119	-0.123	-0.082
	(0.000)***	(0.070)*	(0.000)***
MARGINAL	0.090	0.045	0.067
	(0.051)*	0.649	0.158
BACKGROUND	0.040	-0.021	0.020
	(0.082)*	0.739	0.315
TARGET	-0.024	0.063	-0.005
	(0.042)**	(0.050)*	(0.584)
log(IPC4_C4)	-0.095	0.116	-0.039
	(0.062)*	(0.444)	(0.329)
IPC4_D10	0.018	0.191	0.046
	(0.733)	(0.091)*	0.340
ES	0.046	0.010	0.030
	(0.166)	(0.908)	(0.286)
FR	0.055	-0.099	0.013
	(0.028)**	(0.088)*	(0.466)
IT	-0.009	0.019	-0.002
	(0.617)	(0.687)	(0.880)
UK	0.142	-0.271	0.019
	(0.000)***	(0.000)***	0.171
log(CLAIMS_GRANT)	0.016	0.022	0.013
	(0.072)*	(0.399)	(0.070)*
OPPOSITION	0.050	0.042	0.039
	(0.010)**	(0.399)	(0.019)**
OBS_III_PARTY	0.097	0.117	0.090
	(0.194)	(0.382)	(0.178)
log(STATES)	0.033	0.024	0.024
	(0.003)***	(0.380)	(0.005)***
AppYear Dummies	Yes		
TechClass Dummies[a]	Yes		
Macro_TechClass Dummies[a]	Yes		
N	6156		
Ll	-3398.527		
chi2	91.070		
Athrho	0.081		
	(0.926)		
predicted prob.	0.166	0.616	0.102

* p<0.10, **p<0.05, ***p<0.01.

p-values in parenthesis, based on robust standard errors adjusted for clusters by firms' identifier.

[a] For the identification TechClass dummies are included only in the selection equation and MacroTechClass dummies are included only in the selected equation.

The probability of selection is the analogue of the probits in the previous Section. There we estimated the impacts of the covariates on the probability of an actual license (i.e. LICENSE = 1), while here we estimate the probability that a patent holder offers the technology on the market (WILL_LICENSE=1). Since the latter set overlaps to a good extent with the former, the marginal effects of the probability of selection are similar to those in Table 3. In particular, we find that our measures of protection (CLAIMS_GRANT), generality (NIPC4), scientific intensity (SCIENCE_LABS), value (OPPOSITION, STATES), competition (C4_IPC4), and marginal technologies (MARGINAL) are statistically significant, and have the expected sign. Moreover, here as well, the firm size effects (LARGEFIRM, MEDIUMFIRM) are statistically significant, and they are the most sizable impacts. This confirms that size and the ownership of downstream assets is a key reason for not licensing. We also find a negative and significant sign of our measures of the structured nature of the project, TARGET, which we did not find in the previous estimations. This confirms that planned and structured projects are pursued to develop new products internally. Finally, BACKGROUND still has a smaller impact than MARGINAL as in the previous Section, but its statistical significance is now higher.

An interesting difference is that the UK dummy is now sizable and statistically significant. This is consistent with some simple statistics. In our sample of 6156 patents (which exclude the Dutch inventors), the share of UK patents (by country of first inventor) with WILL_LICENSE = 1 is 31.6% against 14.3% for Germany, 14.1% for Italy, 19.5% for Spain, and 21.4% for France. The share of patents with LICENSE=1 are 14.3% for the UK, 9.7% for Germany, 10.0% for Italy, 12.8% for France, 13.6% for Spain (and 13.8% for the Netherlands, since we have the Dutch information in this case). The actual licensing shares are still higher for the UK, but the difference is much smaller. Because the firm size dummies do not control for differences within each size category, the UK effect may stem from uncontrolled differences in firm size compared to Continental Europe. In fact, the dummy for the medium firms is smaller, but not that different from that of the large firms. This suggests that the effect of size occurs to a good extent when a firm overcomes a threshold of minimal production and commercial capabilities. A more convincing interpretation is that the functioning of markets is more efficient in the UK than in Continental Europe, including lower transaction costs in the market for technology and a more developed firm culture for new business models like business licensing. This makes licensing closer to an arms-length market transaction. Companies then take licensing decisions more lightly. By contrast, in the more traditional Continental European setting licensing is a more planned event, often between larger firms involving interactions and more complex exchanges among the parties closer to a collaborative agreement than a pure market transaction. In these cases, when the companies decide to license, it is because they have pondered the opportunity seriously which raises the odds of the license actually occurring.

The conditional probability results are the novel feature of the Heckman probit estimation. Table 4 shows that most of the conditional effects are small and statistically insignificant. The licensing opportunities seem to be in good part anticipated by the seller in her decision to license. There are however exceptions. First and foremost, the larger firms are less likely to license even after they choose to license. The large firm dummy is sizable and significant, like in the previous case. The medium firm dummy has a similar impact, even though less statistically significant. Again, more than size *per se* the effect seems to be associated with some minimal production and commercial capabilities. In this respect, one potentially unanticipated factor is that when the licensor has production and commercial assets, the licensees fear that they may be affected by his competition in the same final market, considering that the licensor also has better knowledge and experience with the technology. The bigger and more significant impact of the large-firm dummy suggests that in any case the effect is higher and better measured when the licensors are larger firms.

Another exception is that there is a slightly significant negative effect for the patents that rely on the scientific literature. More academic patents, which are likely to be more basic, find fewer opportunities to be used economically. We also find that targeted research, which was less likely to be offered in the technology market, is instead more likely to be licensed if the licensor chooses to do so. We noted that targeted research is planned and pondered, which is associated with a greater internal use. But for the same reason, any decision to license is equally planned, which makes it more likely that the technology is sold. This may even capture our earlier point that in Continental Europe licensing is a more seriously weighed choice. Thus, if the goal is stated, it is more likely to be achieved. Finally, the UK dummy is negative, sizable and significant. This mirrors our earlier discussion about the transaction costs and other factors that may raise the UK's probability that the patent holders want to license, but reduce their ability to actually do so.

The third column in Table 4 reports the marginal effects on the probability of licensing. There is no need to discuss these results in detail as the marginal probability of licensing is the product of the previous two probabilities, and the marginal effects are equal to the sum of the marginal effects of the previous two columns weighted by the predicted value of the other probability, which is also reported in Table 4.[3] Note only that the large firm dummy is almost twice as big (in absolute terms) as the medium firm dummy suggesting that some continuous scaling effect is present.

5 Discussion and Conclusions

We employed a novel and rich dataset built from an extensive survey of European patents to study the determinants of the firms' decision to license and the actual occurrence of the licensing event. Our results confirm previous findings in the literature, and provide some additional empirical evidence. The probability of licensing is higher in the case of greater protection and more codified or general knowledge. It is also higher when there are more potential technology suppliers, and when the patent is of greater economic value. The latter result suggests that there is no "lemon" problem in the market for technology.

Moreover, we find that all the factors above significantly affect the willingness to license, but only a few of them affect the probability that the licensing event occurs. This suggests that the sellers know which patents can be potentially licensed. For example, they do not offer patents that are not valuable or that are not relatively broad. In turn, because generality, value, protection, or non-core technologies do not affect the actual probability of licensing, they cannot be responsible for the lack of realized technology transactions.

To conclude, a useful way of summarizing our findings is to discuss their implications for the opportunities for increasing the size of the markets for patented technologies, and the extent to which policy actions can help this process. In this respect, our analysis produced three main findings.

First, there are transaction costs in the market for technologies that prevent a licensing agreement being concluded. Since we have controlled for several factors that may affect technology trade, our evidence agrees with Razgaitis' (2004) study which shows that the reasons why many licensing deals are not concluded depend on subtler and harder-to-observe elements such as the inability to find buyers, the difficulty in getting internal approval to conclude the deal, disagreements on exclusivity or geographical restrictions. If the failure to license was correlated to the value of the patents or other covariates in our regressions, there would be little room for enhancing the actual size of the market for technology compared to its potential. The patents that are not licensed would simply have characteristics that make them less appealing.

[3] That is P(LICENSE=1, WILL_LICENSE=1) = P(LICENSE=1 | WILL_LICENSE=1)*P(WILL_LICENSE=1), and therefore its derivative with respect to any covariate is the sum of the derivative of the first term (i.e. its marginal effect) times the second term and the derivative of the second term (its marginal effect) times the first term.

But we find that the failure does not depend on many observable factors that we included in our regressions, which cannot then explain why a large share of potential licenses is left untapped.

Our evidence is then consistent with the view that the development and the efficient functioning of markets require supporting institutions, as noted for instance by Rosenberg and Birdzell (1986) in a historical setting, and by Arora et al. (2001) in the particular case of the markets for technology (see also David, 1993a, 1993b, 1998). These institutions will arise and co-evolve with the growth of markets for technology. Experience with technology contracts will make them easier to write and more standardised. Moreover, if these markets grow, intermediaries will arise profiting from the opportunity of matching buyers and sellers, thereby reducing their failure to meet, like in the US XIX century patent market discussed by Lamoreaux and Sokoloff (1998). Policy can of course help, but in our opinion it should not take the form of creating such intermediaries. It should rather remove any obstacle that prevents the supporting institutions coming into being, or it should support their formation when they have difficulties emerging. Moreover, especially at their outset, markets are not very good at providing the economic agents with the right incentives to coordinate in order to create such institutions (e.g. proposing legal standards for technology contracts). Policy can sustain or accelerate this coordination.

Our second finding is that the size of the firm is by far the most important determinant of both the propensity to license and the actual licensing. Small firms are orders of magnitude more likely to license than large firms. Quantitatively, the effect of the firm size is much higher than all the other covariates. The probability that a large firm offers a patent for licensing is about 19% lower than a small firm, while the conditional probability of an actual license is about 15% lower. In relative terms the effect is much greater in the former case, as the average share of patents offered for licensing in our sample of 6156 observations is 18.4% (25.3% for the small firms *vs.* 9.0% for the large firms), while the average conditional probability of an actual license in the same sample is 59.4% (68.0% for the small firms *vs.* 55.4% for the large firms). In this respect, our findings about what could enhance the markets for technology are pretty clear. They thrive when there is technological entrepreneurship, when the environment is germane to the formation of smaller technology-based firms, and more generally when there are such smaller technology specialists that are more likely to find it profitable to sell the technology rather than investing in the downstream assets to become a fully-fledged final producer. This same point was also made by Arora et al. (2001). Yet, this paper showed that the order of magnitude of this effect is notable both *per se* and compared with other factors that may raise the utilization of the market for technology. In addition, this has implications for the rate of patent utilization. A first-order factor that may raise it, is whether industries are organised around smaller technology-based firms as opposed to being based mainly in large integrated corporations. In short, the underlying organisation of the industry may seriously affect the rate of patent utilization. Thus, ultimately, the policies that are often advanced to favour the formation of technological entrepreneurship, or to sustain technology-based small firms, may have the additional advantage of raising the economic use of patents.

Our third finding is that not only are the large firms less willing to license their technologies, but they are also less likely to license when they choose to put their technologies in the market. The results of our regressions show that among the few factors that prevent the completion of a licensing deal when the supplier is willing to license, the most important one is by far the size of the firm. The potential licensee may enjoy lower rents from the license because the large firm is an important competitor in the final market of that technology, or it could simply push the licensee into a niche market. Another possibility is that the large firms have internal licensing departments, which reduces the marginal cost of offering new licenses. Hence, they offer a larger number of licenses and on average put less effort into concluding each licensing deal. Our result that the large firm dummy has a negative impact on the conditional probability as well suggests that large firms do not anticipate these difficulties in the market for technology when they decide to license.

From a policy perspective, these impediments are less straight forward to remove compared to the previous ones. The large firms are repositories of under-utilized technologies, as Rivette and Kline (2000) pointed out. Their willingness to license may increase if licensing becomes a profitable opportunity. Yet, compared to a smaller firm, it is more difficult to increase their rate of actual licensing because they have to reduce the perception that they may compete with the licensee. This may be hard to do for a firm with sizable production or commercial assets, and with market power. The large firms could put more effort into selling their licenses. Yet, to the extent that they find it profitable to organize activities on a large scale, and they set up internal departments to do so, a small marginal cost of offering new licenses, with implied lower effort per licensing deal, might be physiological. At the same time, this means that policy cannot do much to increase the actual licensing rate of large firms without important changes in the way they deal or organize their licensing business. The formation of independent concerns, like *yet2.com* in the US, which specialise in licensing, and many large firms have used as their technology sales agent, may be one way to go. The independence of the companies from the large firms might provide some insurance to the licensees that the supplier will not directly compete with them. Moreover, the specialisation of the company might improve the managerial efficiency of the technology trade activity. A more thorough analysis of these issues is left to future research. Our finding simply suggests that just putting the technologies of large firms into the market is not enough. It has to be accompanied by a more systematic assessment of licensing as a business, and a careful definition of the strategies and the organizational models that can make it into a profitable economic activity.

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APPENDIX

Table A.1 Descriptive statistics - technological classes

	Mean	St. Dev.
5 Macro Technological Classes		
Electrical engineering	0.158	0.365
Instruments	0.100	0.300
Chemistry, Pharmaceuticals	0.185	0.388
Process Engineering	0.253	0.435
Mechanical Engineering	0.305	0.460
30 Technological Classes		
Electrical devices, electrical engineering, electrical energy	0.077	0.267
Audio-visual technology	0.019	0.137
Telecommunications	0.031	0.174
Information technology	0.021	0.143
Semiconductors	0.010	0.099
Optics	0.018	0.134
Analysis, measurement, control technology	0.056	0.230
Medical technology	0.021	0.145
Organic fine chemistry	0.058	0.234
Macromolecular chemistry, polymers	0.057	0.232
Pharmaceuticals, cosmetics	0.017	0.128
Biotechnology	0.005	0.068
Materials, metallurgy	0.033	0.178
Agriculture, food chemistry	0.012	0.109
Chemical and petrol industry, basic materials chemistry	0.036	0.185
Chemical engineering	0.029	0.167
Surface technology, coating	0.017	0.128
Materials processing, textiles, paper	0.057	0.231
Thermal processes and apparatus	0.023	0.148
Environmental technology	0.016	0.124
Machine tools	0.038	0.191
Engines, pumps, turbines	0.029	0.169
Mechanical Elements	0.044	0.205
Handling, printing	0.082	0.274
Agricultural and food processing, machinery and apparatus	0.020	0.141
Transport	0.073	0.261
Nuclear engineering	0.004	0.064
Space technology weapons	0.006	0.076
Consumer goods and equipment	0.049	0.216
Civil engineering, building, mining	0.043	0.203

Number of observations=7105.