University IPRs and Knowledge Transfer. Is the IPR ownership model more efficient?

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Abstract
We employ data from a large scale survey among inventors of European patents to assess whether university-owned patents in Europe are more often applied, and/or more economically valuable, than patents that result from university research but are not owned by universities (university-invented). Our analysis starts from the observation that in our sample of six major European countries, relatively many patents that result (at least partly) from university research, are not owned by universities (but instead by private firms). A review of the theory of research joint ventures suggests that ownership is the result of a bargaining game, in which the relative bargaining positions depend, among other things, on characteristics of the inventive process. This is the starting point for applying two separate statistical treatment models. Our results indicate that, after correcting for observable patent characteristics, there are no significant differences between university-owned and university-invented patents.

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1. Introduction

Universities are playing an increasing role in the production and distribution of knowledge in all the OECD countries. Major institutional changes have been carried out in various countries following the idea that the university had to have a more proactive way in transferring knowledge to industry. In most policy circles an oversimplified vision of the "winning" American model based on the research university that owns the property rights on its inventions and actively seeks to exploit them has been taken as the new way forward. Specifically, most of the policy attention has focused on the need for European countries of a 'Bayh-Dole Act'-like legislation disregarding all the other policy actions (specifically on IPR regulation) carried out in the US during the eighties and nineties that could explain at least partially the high patenting activity of US universities (Mowery et al, 2004).

While a large number of works have been produced on various aspects relevant to the understanding of the economic behaviour of university knowledge production and distribution, very little is still known on the relative efficiency/effectiveness of the various knowledge transfer channels. Patenting has become to be seen as an efficient/effective way of transferring knowledge, but very little evidence (if at all) has been put forward to support this claim. Similarly, the ownership of the patent by the university is presented as the best configuration to maximise the transfer of knowledge, however no evidence exist of this.

This paper aims to fill this gap. We focus on patenting as one channel of knowledge transfer without studying its relative efficiency/effectiveness compared to other channels (such as contract research or researchers mobility) and we analyse the relative efficiency/effectiveness of different ownership configurations. Specifically, we compare *university-owned* patents (those patents that have a university assignee) with *university-invented* patents (those patents that have at least one university inventor). We employ data from a large scale survey among inventors of European patents (PatVal database[1]) to assess whether *university-owned* patents in Europe are more often applied, and/or more economically valuable, than *university-invented*.

The paper is organised as follows. In Section 2 we review the theoretical analysis of IPR ownership in the context of research joint ventures and present our hypotheses. The data sources and descriptive statistics are presented in the Section 3. Sections 4 and Section 5 respectively put forward the methodology used and present the results. Finally, the main result pointing to a lack of significant differences in the use and value of university-owned and university-invented patents discovered is discussed in relation to current policy actions in the conclusions.

2. University IPR Ownership and Technology Transfer

Much of the current debates on the technological competitiveness of Europe centres, correctly or not, around what is known as the 'European paradox': Europe performs well in scientific research, but is bad in commercializing it (European Commission, 1995).[2] Naturally, as an outcome of the central role of this 'paradox', emphasis has been put on the nature of industry – science relations in Europe. The suggestion is that these relations leave much to determine, and that policies are needed to make them more efficient.

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[1] For more information on the PatVal Project, see Giuri, Mariani et al. (2005).

[2] The concept of an existence of a European paradox has been challenged by scholarly work in recent years. See for example Brusoni and Geuna (2003), Tijssen and van Wijk (1999) and Dosi, Llerena and Sylos-Labini (2005).

From an economic point of view, what could be the reasons for such underutilization of academic research in private businesses? Quite a few academic and policy works have suggested that European academic IPR set up, or the lack of a strong enforcement of it, can be considered one of the major causes of the supposed low contribution of science to innovation. However, only very few theoretical works (and even less empirical validations) have addressed this issue putting forward an analytical framework to assess if and when the lack of (strong) IPR, or the inappropriate assignment of it, can be considered as the cause of underutilisation of academic science.

To the best of our knowledge, only the papers of Aghion and Tirole (1994), Hellman (2005) and Mazzoleni (2005) have developed full economic models to assess the impact of academic IPR on the efficiency of the development process. Starting from the observation that efficient contracting cannot be assumed in this context and therefore the Coase theorem does not apply, Hellman (2005) develops a search and matching model that, on the basis of an ex-post (discovery) assessment of searching costs, identifies the condition under which academic patenting would help in "bridging" the "gap" and therefore result in a more efficient system. The paper only indirectly considers the issue of the assignment of property rights when considers the role of technology transfer offices making the assumption that the patents is owned by the university. Mazzoleni (2005) analyses the social welfare implications of academic patenting focusing on the appropriability conditions of downstream R&D. It compares the two scenarios of 'open access' and 'licensing'. The first is characterised by diffusion of knowledge through traditional open science channels while the second relies on academic patents. The paper is very much informed by the American context and does not take into account the issue of ownership of the property right.

The paper by Aghion and Tirole (1994) instead focuses squarely on the issue of the ownership of intellectual property rights. They argue that in the case of joint research projects between universities and private firms, the assignment of property rights (patents) to the firm instead of the university may lead to market failure, i.e., the innovation resulting from the collaboration has a lower value than could have been the case if the university had owned the patent. Given our interest on comparing models of IPR ownership rather than examining the overall efficiency of academic patenting, in the following we discuss the prediction of the Aghion and Tirole model to set the basis for our empirical investigation.

In the Aghion and Tirole model, a university undertakes a research project for a private firm. Both parties need to invest in the project, and the relationship between both investments and the probability of success (i.e., an innovation) is given by a concave function. Due to the uncertainty, the actual content of the innovation is non-negotiable ex ante. Therefore, the contract specified for the research project is incomplete: it specifies only the attribution of the property right (who owns the patent, the university of the firm?), the license fee that the university obtains in case the patent is assigned to the firm, and the amount of investment of the firm. As an assumption, only one of the two parties involved may own the patent resulting from the project. The model assumes profit/utility maximization by both parties.

In this setting, the pay-offs of the invention to the two parties are related to ownership. If the firm owns the invention, the university does not share in the profits from the invention. Instead, it is paid a pre-bargained fee that covers its research efforts. On the other hand, if the university owns the invention, both parties share the pay-off by means of a licensing fee levied by the university. The university and the firm bargain ex ante over ownership of the expected invention, taking into account these (expected) benefits. Then, the answer to the question who will own the patent depends on two factors: the relative marginal impacts of the research efforts of both parties, and the ex ante bargaining power of both parties. We discuss both factors in turn.

The relative marginal impacts of the two parties are important because the university only has an incentive to make the maximum effort in case it owns the patent. Due to the incompleteness of the research contract, the firm does not have the means to control whether or not the university makes the maximum effort. Thus, if the university does not own the invention, it's best strategy is to 'shirk', i.e., provide a minimal research effort. Such a shirking university is obviously a problem for the firm, because it will lead to a less valuable invention. If the relative marginal impact of the university's research effort is large, this becomes a serious problem, and the firm is therefore likely to leave ownership to the university.

In the formal model, Aghion and Tirole compare the pay-offs to the firm under both modes of ownership. If the firm owns the patent, it gets the full amount of pay-offs (net of the lump sum payment to the university). If the university owns the invention, the firm gets only part of the total payoff. Thus, the firm compares a shared pay-off under maximum effort by the university to the full pay-off with a 'shirking' university. Obviously, the higher the marginal impact of the university effort, the more likely it is that the first of these situations will lead to a higher pay-off for the firm. Thus, the higher the marginal impact of the university effort, the higher the willingness of the firm to leave ownership of the invention to the university.

Bargaining power for the university also influences the assignment of the patent. For example, if the university has specific knowledge that makes it a research monopolist, the firm may have to choose between no project at all (and hence no pay-offs) and sharing pay-offs with the university. As long as the shared pay-offs are positive, the firm will then still undertake the research project and leave the patent to the university (which would be socially optimal).

A case of market failure may emerge when the university does not have strong bargining power and the relative marginal impacts of the two parties are such that the firm is unwilling to leave the patent to the university. To see how this emerges, let us call the value of the innovation under firm ownership of the patent (i.e., minimum effort by the university) $\mathbf{V}^{\mathbf{0}}$. Now *assume* that the extra effort that the university would be willing to make in exchange for ownership leads to an increase in the invention value equal to $\Delta > 0$. Obviously, as long as $\Delta > 0$, the social value of the innovation goes up with a transfer of the patent to the university. But, because in this case the firm only gets a share of the invention value, its private pay-off may be lower. Assume the firm gets a share σ (Aghion and Tirole assume $\sigma = ½$). Then, $\sigma(\mathbf{V}^{\mathbf{0}} + \Delta) < \mathbf{V}^{\mathbf{0}}$, or $\Delta < \mathbf{V}^{\mathbf{0}}(1 - \sigma)/\sigma$ would be sufficient to withhold the firm from making the socially efficient decision to leave the patent to the university.

The extra effort of the university need not always lead to a larger value of the invention ($\Delta > 0$) because the effort of the firm is endogenous. Then, the optimal firm effort may go down as a result of increased university effort. In such a case, market failure does not take place, and the allocation of the patent to the firm is optimal.

Note that market failure only results if the university is cash constrained, which is an assumption of the model, and the firm has a large degree of bargaining power. If the university would not be cash-constrained, it would be able to pay the firm the difference $\mathbf{V^0} - \sigma(\mathbf{V^0} + \Delta)$ and still have positive pay-offs itself. Because the firm is not assumed to be cash constrained, market failure is not a possibility in case the university owns the patent (e.g., when it has high ex ante bargaining power).

Whether the strong assumption on pay-off maximizing and cash constrained universities is realistic, can be debated. As long as the firm behaves in a strictly profit-maximizing way, market failure due to a lack of university ownership of patents is a possibility. Arguably, in the framework of the Aghion and Tirole model, universities not being interested in monetary pay-offs only reinforce the possibility of market failure.

What can be done about the market failure due to a 'wrong' assignment of patents resulting from university – private research collaboration? The fact that the market failure is asymmetric (only firms owning patents can be inefficient) makes it possible to eliminate the sources of market failure by giving universities more bargaining power, for example by a piece of legislation like the Bayh-Dole Act that was introduced in the U.S. in 1980 (Eisenberg, 1996, provides an overview of the debates surrounding the introduction of the Bayh-Dole Act). This law provides universities in the USA with the right to own patents on research that was sponsored from federal sources such as the National Science Foundation (NSF).

The usual economic logic behind the Bayh-Dole Act (for an overview, see, e.g., Mowery et al., 2001) is that these patents will facilitate technology transfer from universities to private firms. When university research generates knowledge that may be applied in commercial products or processes, private firms may be interested in this knowledge. But when it comes to making additional investments in order to transform the university-generated knowledge into a commercial application, an additional incentive problem may pose itself. A firm that endeavours to undertake the additional R&D that is necessary to develop the commercial application will only consider this a useful undertaking when it has a prospect of deterring imitation by competitors. This is only possible if the firm that develops the applied knowledge to turn the university discovery into a commercial application has an exclusive right to do so. Otherwise competitors may move in, and use the freely available university knowledge to develop a competing application, and this prospect is enough to discourage private investment following up university research. The only way in which the firm that wants to develop the university discovery may obtain exclusivity, is when the university patents its discovery, and grants an exclusive license to the firm.

Note that this argument is somewhat more extensive than the setting of the Aghion and Tirole model discussed above. It sketches a two-stage research process, with the university undertaking the basic research, and the firm the applied (or experimental) research, whereas the Aghion and Tirole model considers a research joint venture. The 'common logic' also does not pose the question of ownership of the patent (either the firm interested in the research, or the university itself). Since we are primarily interested in the issue of ownership (for empirical reasons discussed below, we prefer to use the Aghion and Tirole line of argument, but we notice that this leads to the same conclusion, i.e., that universities should be stimulated legally to patent their inventions, as the common argument in the Bayh-Dole debate.

Note also that there is a subtle difference between the US context of the Bayh-Dole Act and the situation in European nations. In the US, because of its federal structure, a specific question with regard to ownership of federally sponsored research had emerged (Mowery and Sampat, 2001). Funding bodies such as the NIH and NSF could claim rights because they (co-)financed research, and universities could equally do so because they financed part of the research themselves, and because they employed the researchers and owned the labs in which the research was done. U.S. law did not provide an immediate and clear answer as to who held the rights to patent federally funded research. Hence the funding bodies and the universities usually engaged in complicated negotiations over these rights. First, these negotiations were taking place on a case-by-case basis, but later on so-called Institutional Patent Agreements (IPAs) were introduced by the larger funding agencies. The Bayh-Dole act was introduced in order to streamline the multiple arrangements in this field.

A phenomenon like the IPAs found in the US is (still) largely unknown in Europe, because of the absence of large funding organizations as found in the US. Instead, a different issue seems to emerge with regard to the patenting of European university research. In some European countries Bayh-Dole act like regulation giving the ownership of IPR to the university instead of the professor (professorial rights) has been in force for many years (though possibly not enforced), while in other countries it has been introduced only recently in an emulation of the Bayh-Dole act. Across European countries (except Italy) there is now strong support for the assignation of IPR ownership to the university based on the view that this policy can help solving the "European paradox". The evidence usually put forward is that European universities have much less patents than US universities therefore there is need of new regulation to create incentives for them to be more active. In this paper we endeavour to examine the validity of this rational using the Aghion and Tirole framework to study new original data on university patenting in Europe gathered in the Patval survey.

3. A First Assessment of European Academic Patenting

For our empirical analysis we rely on the Patval survey. For a full description of the survey sample, methodology, and a preliminary analysis of the response see Giuri, Mariani et al. 2005. The survey was addressed at inventors listed on (granted) European patents with a priority date in the period 1993 – 1997, in six European countries: Germany, France, Italy, The Netherlands, Spain and the UK. These six countries accounted for about 80% of granted EPO patents, whose first inventor has an address in of the EU-15 countries. The survey was carried out in the period July 2003 - April 2004. We obtained responses relating to 9,017 patents representing 18% of all granted EPO patents with a priority date in the consider period.

On the basis of a question that asked where the inventor was employed at the time of the invention, we were able identify 433 patents in which at least one of the inventors was employed by a university (we will label these '*university patents*' from now on). They represent 4.8% of our sample. Table 1 presents, for each country in the sample, the total number of patents and it breaks down ownership of the patent into university or non-university. *University-owned* patents are those patents that have a university assignee, while *university-invented* patents are those patents that have at least one university inventor but they are not owned by a university. What the table brings out very clearly is that the large majority of patents in which university inventors were involved is not owned by universities (but instead mostly by private firms).[3] In all countries except Spain, the fraction of *university-owned* patents in *university patents* is far below half.

[3] See Geuna and Nesta, 2006 and references cited in their paper for preliminary evidence of this phenomenon in a few European countries.

Table 1. Ownership of European *University Patents*

	Germany	Italy	France	UK	Spain	Nether-lands	Total
Total number of *University patents*	108	50	60	139	17	59	433
# *University-owned* patents	4 (4%)	2 (4%)	4 (7%)	46 (33%)	9 (53%)	12 (20%)	77 (18%)
# *University-invented* patents	104 (96%)	48 (96%)	56 (93%)	93 (67%)	8 (47%)	47 (80%)	356 (82%)

The first important contribution this paper wants to make is to compare the US university technology transfer system with our own data on Europe to assess if there is indeed a major difference between the patent output of US universities and European universities (here represented by our sample). Some commentators have argued that Europe is 20 years behind the US referring to the Bayh-Dole as the departure point of a new technology transfer model that Europe needs to follow to support a more significant contribution of European universities to the innovative process of firms. In other words, European universities do not produce a sufficient number of patents (based on national and OECD statistics of university-owned patents) and therefore they are not efficient in technology transfer.

If we look at US data for the period 1993-1997 we discover that academic patents accounted for between 1.9% and 4.3% of US PTO patents depending if we considered all US-PTO patents or only the one assigned to US organisations (private and non-profit) (NSF, 2004). If we assume that our European *university patents* sample is representative of the total population or academic EPO patents it is clear that European universities are not performing in an inferior way compare to US universities. Also assuming a response bias in favour of academic inventors would not change the picture in a systematic way. Why our results differ in such a dramatic way compare to the commonly accepted policy view of a technologically low performing higher education system in Europe? The most important reason is that official data take only into account *university-owned* patents therefore underestimating in a macroscopic way the activity of European universities.

Can we find a way to adjust the US data to take into account of the ownership issue? The US NSF data take into account only *university-owned* patents, however, a recent work by Thursby et al (2006)[4] has put together information at the inventor level controlling for ownership for 87 research intensive universities accounting for about 6,000 patents in the middle 1990s. Table 2 presents an elaboration of their data.

Table 2. Ownership of US University Patents

	Share of total academic patents
Total number of *University patents*	?
# *University-owned* patents	66%
# *University-invented* patents	32%
US federal government as one of the assignees	2%

Author elaboration of data from Thursby et al (2006).

[4] We want to thank Jerry Thursby for having allowed us to access their data on the US system before publication.

Though we acknowledge that the two sample may be not perfectly comparable, the first striking observation that can be made looking at the two tables is that while in the US about 2/3 of *university patents* are owned by the university that employed one of the inventors, in Europe university ownerships accounts for less than 1/5. These data seems to point to the existence of two different model of university technology transfer. The American model is mainly based on the university owning the rights to the discovery made by one of its academic employees; on the basis of this right, the university commercialises the discovery via the technology transfer office (TTO) effort to licence or create a spin-off. Instead, the European model of academic technology transfer is mainly based on a direct transfer of property rights from the academic inventor to the assignee of the patent (usually a large firm) with only a minor role for university ownership and TTOs activity in licensing or spin-offs.

One may argue that the figures presented here clearly show the incentive creation effect that the Bayh-Dole had on the US system. This would be the case only if the US system had a much higher academic patents productivity in the middle 1990s compared to Europe. However, if we adjust the data for the US taking into account that the official statistics underestimate of about 1/3 the number of *university patents* (generalising the result of Table 2 that about 1/3 of patents had an academic inventor but were not owned by the university), and we recalculate the two shares of academic patents on US-PTO patents present above, we would end up with a bracket 2.5% - 5.7%. Also assuming that the upper bracket is the correct one and comparing this figure with the 4.8% from out sample (assuming that all EPO patents are owned by European organisations) we could conclude that US academic patent productivity is about 15% higher than the European. However, if we compare with the lower bracket (in this case we would assume that the EPO system is as internationalised as the US-PTO) we would conclude that the European academic patent productivity is about 45% higher than the US.

These back-of-the-envelop calculations aim to make the point that once you adjust the data for the ownership structure, thus taking into account the different university technology transfer models, it is not so clear that the US system is outperforming the European system. In absolute levels US universities did have more patents in the middle 1990s compared to European universities, however they did not have a significantly higher share of national patents. This result questions the impact that the Bayh-Dole had on the US academic system. Our data seems to be consistent with the evidence put forward by a series of papers of Mowery, Nelson, Sampat and Ziedonis[5] that argued that the increased number of university patents is mainly due to the coming up of the new technological opportunities offered by biomedical and ICT research as well as the general trend in increased appropriability and patentability of the US-PTO. Preliminary evidence put forward for Germany and Italy (Geuna and Nesta, 2006) seems to indicate that also European universities have responded to increased technological opportunities as showed by the increased number of *university patents* in the 1980s' and 1990s'. While, one of the reasons for a lower absolute level of university patents can be found in the different characteristics of the EPO system, lower funding levels of higher education research in EU countries and a smaller size of the HE system in the EU.

3.1 Technology transfer and market failure

Apparently, although European universities are involved in research with commercial value (i.e., leading to patentable inventions), do not particularly care to exploit the results of this

[5] Mowery et al (2004) for a summary for their results.

research by means of owning the associated patent. As the review of the Aghion and Tirole model above suggests, a lack of university bargaining power or a relatively low marginal contribution of university efforts to the outcome of the research projects may be responsible for this. We may take the distribution of inventors over the two parties as an indication of the relative marginal impact of research efforts. Table 3 provides information on this variable for the sample of 384 patents for which we have this information. In this sample, slightly less than half (45%) of all patents has only university inventors. 55 % of all patents has university inventors and non-university inventors.

Table 3. Ownership and inventorship of university patents

	Only university inventor(s)	University inventor(s) and other type inventor(s)	Total
University-owned patents	53 (31% of column)	11 (5% of column)	64
University-invented patents	119 (69% of column)	201 (95% of column)	320
Total	172 (45% of row)	212 (55% of row)	384

Within the group of patents that has non-university inventors, only 5% of patents is *university-owned*. Within the group of patents with only university inventors, this percentage is larger (31%), although still clearly less than half. Thus, overall, we see a tendency for firms to own the patent resulting from joint research with universities. However, if we take the distribution of inventors over the research partners as a (broad) indication of relative marginal research impact, the data seem to support the idea from the model that this variable has an impact on the distribution of ownership of the invention.

This preliminary result suggests that 'the market' indeed deals with the question of ownership of intellectual property rights in case of public-private research joint ventures. However, as the Aghion and Tirole model shows, such market exchanges of patent ownership may still be prone to market failures. Since we have data on the (perceived) value of inventions,[6] we are in a position to test for the existence of such market failure.

In doing so, we make use of the outcome of the Aghion and Tirole model that market failure occurs in an asymmetric way: if the market fails to provide the optimal innovation size, it is because the firm takes ownership where this should have been assigned to the university. Thus, if market failure plays a significant role, we would expect that, ceteris paribus, the value of patents would be lower for the sample where firms own the patent than for the sample where universities own the patent (in this case, the model predicts that the market produces the optimal innovation value). Thus, we formulate our research question as follows: can we find, ceteris paribus, the factors that impact on ownership of patents resulting from public – private research joint ventures, a positive effect of university ownership on the economic value, and/or the rate of commercial application of patented inventions? If the answer to this research question is positive, this amounts to support for a “European Bayh-Dole Act”.

4. Descriptive statistics

There are 433 university related inventions in the PatVal dataset, 77 (18%) of them owned by the university and 356 (82%) owned by a firm or another non-university public research organisation and governmental bodies.[7] Before proceeding with the analysis it is important to

[6] For discussion on the robustness and use of the information on the (perceived) value of invention see Gambardella et al. (2005).

[7] Firms own about 65% of these patents.

study the characteristics of both sub samples along a long list of explanatory variables capturing both invention and inventor's backgrounds. We define these variables in Table 4.

[Insert Tables 4 & 5 about here]

The results of this exercise are summarised in Table 5 where the main variables are previously classified in 5 blocks: country effects –according to where the research leading to the invention was located–, technology effects –according to the patent main IPC at 4 digit–, inventor's background – a set of variables with background information of the inventor answering the questionnaire–, invention background –a set of variables with information about some characteristics of the invention leading to the patent–, and, finally, the impact block –with a set of impact variables focus of interest. We describe each one of these blocks in the remaining part of this section.

The results regarding the Country blocks show that there are major differences between both sub samples in the distribution of patents across the different countries. Indeed, while almost 60% of the university owned patents are based in the UK, this figure is just 26% for the other group (the university invented but not owned patents). There are also significant differences in the distribution of both types of patents in Germany (5% owned only vs 29% in the control group), Italy (2.6% of owned patent, but 13.5% of patents in the control group), Spain (11.7% of owned patents but 2.2% in the control group) and France (5% of owned patents but 15.7% in the control group). All of these differences are statistically significant at the conventional levels. The only country with a balanced proportion of both types of patents is Netherlands (15 % of owned patents, 13% of patents in the other group).

Despite the major differences in the distribution of patents across countries, the results regarding the technology effects more balanced. Indeed, the only technology class where we were able to reject the null hypothesis of equal participation was Instruments, with 32% of university owned patents but only 18% of patents in the other group. Regarding the differences in the distribution of inventor's characteristics across both sub samples of patents, we also observe a very balanced pattern. The only two exceptions are regarding the variable Tenure, where the mean is higher in the non-university owned group, and the number of EPO patent applications by the inventor, where the mean is also higher in the non-university owned group.

There are more differences regarding to some of the characteristics of the invention process. Here we found that the mean number of man months invested in the invention process was higher in the case of university owned patents (although the actual financial investment was similar). The mean number of applicants and the proportion of patents with multiple applicants were also higher in the university owned patents. On the other hand, the number of inventors was higher in the non-university owned group of patents.

Finally, regarding the impacts, we found that the number of forward citations was higher in the non-university owned group, however the probability of that the patent was actually used is higher in the treated group of university owned patents. Investigating further the reasons for this higher rate of used by university owned we found that this was mainly due to two effects: licensing (55% of university owned patents were licensed with only 15% in the other group) and launching spin-offs firms (22% of university owned patents were also used as a basis for starting-up a new firm versus 8% only in the other group). However, when asked about commercial application, there were no differences between both groups. Similarly, we did not find any differences between the inventor's perceived value of the patent.

5. Statistical methodology

Given our theoretical expectation (based on the Aghion and Tirole model) that ownership of a patent resulting from a research joint venture depends on characteristics of the invention, we cannot rely on a simple test of mean differences in the impact variables to answer our research question. In this section we present the two alternative approaches used in this research to deal with this issue. Both methods have in common that they are based on a selection on observables approach.

5.1 The control function approach[8]

The control function approach rests on the idea that it is possible to identify the average impact of a given 'treatment' (in this case, university ownership) using regression-based techniques conditioning on a large set of explanatory variables that might be correlated with both the treatment and the outcomes. Let us assume that we want to estimate the impact of university ownership on a variable *Y*. This variable can take two values depending on if the sample patent is owned by university or not. More formally:

$$Y_{i1} = \mu_1 + v_{i1} \quad (1)$$

$$Y_{i0} = \mu_0 + v_{i0} \quad (2)$$

where μ captures the impact of a set of control variables, and v captures the gain (or loss) as a result of the treatment. Of course, a given patent cannot be in the two states at the same time, and for this reason we need to approach the non-owned state by using the control group of patents that are not owned by universities. By defining a dummy for the treatment, we can combine (1) and (2) in a unique expression:

$$Y_i = \mu_0 + D_{i,owned}\left(\mu_1 - \mu_0\right) + v_0 + D_{i,owned}\left(v_{i1} - v_{i0}\right) \quad (3)$$

Here is where we introduce the idea of control function. Let us assume that we can approximate the patent-specific shocks, potentially correlated with the outcomes and the treatment, by large set of observed variables plus an unobserved (uncorrelated) term as follows:

$$v_{i1} = X_i\beta_1 + \eta_{i1}, \quad (4)$$
$$v_{i0} = X_i\beta_0 + \eta_{i0}. \quad (5)$$

Model (3) can then be re-written as:

$$Y_i = \mu_0 + \tau D_{i,owned} + X_i\beta_0 + D_{i,owned}\left(X_i\beta_1 - X_i\beta_0\right) + \eta_{i0} + D_{i,owned}\left(\eta_{i1} - \eta_{i0}\right), \quad (6)$$

where the treatment impact is given by $\tau = (\mu_1 - \mu_0)$. Under the assumption that $\beta_1 = \beta_0$ [9], this model can be further summarised:

[8] See Wooldbridge (2002).

[9] This assumption is not strictly necessary, however given that our dependent variables are mainly discrete, this makes the impact estimation easier. If we relax this assumption we also need to include interactions in the

$$Y_i = \mu_0 + \tau D_{i,owned} + X_i\beta + \vartheta_i, \qquad (7)^{10}$$

where the impact of being a university owned patent is now identified under the assumption that this state is orthogonal with respect to the remaining unobserved part of the treatment *shock*. In the empirical application of below we control for the large set of explanatory variables shown in Tables 4 and 5.

5.2 The matching approach

The descriptive statistics from Table 5 suggest that the assignment of the university patents to treatment or control groups is not at random. In this context, the impact estimation may be biased by the existence of confounding factors. Following Becker and Ichino (2002), matching is a way to "correct" the estimation of treatment effects controlling for the existence of these confounding factors based on the idea that the bias can be reduced when the comparison of outcomes is performed using treated and control patents who are as similar as possible given a, hopefully, large set of control variables. Since matching subjects on an *n*-dimensional vector of characteristics is typically unfeasible for large *n*, this method proposes to summarise pre-treatment characteristics of each subject into a single-index variable (the propensity score) that makes the matching feasible.

Following Rosenbaum and Rubin (1983), the propensity score is defined as the conditional probability of receiving a treatment given pre-treatment characteristics:

$$p(X_i) \equiv Pr\left(D_{i,owned} = 1 \mid X_i\right) = E\left(D_{i,owned} \mid X_i\right), \qquad (8)$$

where $D_{i,owned}$=(0, 1) is the indicator of exposure to treatment and X_i is the multidimensional vector of pre-treatment characteristics. Rosenbaum and Rubin (1983) show that if the exposure to treatment is random within cells defined by X, it is also random within cells defined by the values of the one-dimensional variable $p(X_i)$. As a result, the average treatment effect on the treated (ATT) can be estimated as follows:

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control function between the dummy variable for ownership and the remaining explanatory variables, dealing with interactions in probit or logit settings is not as straightforward one can think (see Norton and Ai, 2004 for further details). The intuition from linear models does not extend to non-linear models. To illustrate consider the following probit model:

$$E(y \mid x_1, x_2) = \Phi(\beta_1 x_1 + \beta_s x_2 + \beta_{12} x_1 x_2)$$

The marginal effect of just the interaction term is:

$$\frac{\partial \Phi}{\partial x_1 x_2} = \beta_{12}\Phi'$$

Most researchers interpret this as the interaction effect. However, the full interaction effect is the cross-partial derivative of the expected value of y:

$$\frac{\partial^2 \Phi}{\partial x_1 \partial x_2} = \beta_{12}\Phi' + (\beta_1 + \beta_{12}x_2)(\beta_2 + \beta_{12}x_1)\Phi''$$

Which is clearly different to what we had before. Another implication of this is that the true interaction effect does not vanish even when β_{12} is zero. And even when it is not different from zero, it signs does not necessarily correspond with the sign of the true interaction effect (see Norton, Wang and Ai, 2004 for further details). In other words, the influence of interactions is in some extent already built within the model.

[10] According to this specification the impact estimator will be the "*average treatment effect*" (ate) which under our current assumptions is also equivalent to the "*average treatment effect on the treated*" (att).

$$\begin{aligned}\tau &\equiv E\{Y_{i1} - Y_{i0} \mid D_{i,owned} = 1\} \\ &= E[E\{Y_{i1} - Y_{i0} \mid D_{i,owned} = 1, p(X_i)\}] \\ &= E[E\{Y_{i1} \mid D_{i,owned} = 1, p(X_i)\} - E\{Y_{i0} \mid D_{i,owned} = 0, p(X_i)\} \mid D_{i,owned} = 1]\end{aligned} \qquad (9)$$

where the second expectation is over the distribution of *($p(X_i)$ $D_{i,owned} = 1$)*. Two assumptions are need in order the matching estimator (9) to be valid:

Assumption 1: The balancing of the pre-treatment variables given the propensity score:

$$D_{i,owned} \perp X_i \mid p(X_i) \qquad (10)$$

which implies that observations with the same propensity score must have the same distribution of observable (and unobservable) characteristics independently of treatment status. In other words, for a given propensity score treated and control observations should be on average observationally identical. This assumption can be tested

Assumption 2: Conditional independence given the propensity score:

$$Y_{i1,}Y_{i0} \perp D_{i,owned} \mid p(X_i) \qquad (11)$$

To ensure that the matching estimators identify and consistently estimate the treatment effect of interest, we assume that the assignment to treatment is independent of the outcomes, conditional on the covariates. In other words, we need to assume that the choice of patent ownership be "purely random" for similar patents (Imbens, 2005 and Abadie, Drukker, Leber Herr and Imbens, 2004, for further details). Different from the previous assumption, this assumption cannot be tested[11].

We have made used of two different matching estimators: the Nearest-Neighbour matching and the Kernel matching. Under Nearest-Neighbour matching we take each university owned patent and search for the non-university owned patent with the closest propensity score. The method is applied with replacement, in the sense that a control patent can be a best match for more than one treated patent. Once each treated unit is matched with a control unit, the difference between the outcome of the treated units and the outcome of the matched control unit is computed. The average treatment on the treated impact is then obtained by averaging these differences. More formally, let *C(i)* denote the set of control units matched to the treated unit with an estimated value of the propensity score. Nearest-neighbour matching sets:

$$C(i) = \min_j \left\| p_i - p_j \right\| \quad (12)$$

In order to define the corresponding matching estimator, let also define the weights

$$\begin{aligned} w_{ij} &= \frac{1}{N_i^0} \quad if \quad j \in C(i) \\ w_{it} &= 0 \qquad otherwise \end{aligned} \qquad (13)$$

[11] This assumption is also known as unconfoundedness (Imbens, 2005) or ignorability assumption (Wooldridge, 2002).

Where N_i is the number of nearest controls for university owned patent i. For nearest neighbour matching this typically one unless there are multiple nearest neighbours, which relatively uncommon. The treatment on the treated estimator is given by:

$$\tau = \frac{1}{N^1}\sum_{i\in 1} Y_i^1 - \frac{1}{N^0}\sum_{j\in 0} w_j Y_i^0 \qquad (14)$$

Although the Nearest Neighbour matching method sounds as the most natural way to proceed because all treated patents will find a match, it is obvious that some of these matches will be fairly poor because for some treated units the nearest neighbour may be very far in terms of the propensity score, but despite this it will make the same contribution to the treatment effect as a very good match. The Kernel matching method offers a solution to this problem. Here all treated are matched with a weighted average of all controls with weights that are inversely proportional to the distance between the propensity scores of the treated and the controls. More formally, the Kernel matching estimator is given by:

$$\tau = \frac{1}{N^1}\sum_{i\in 1}\left\{ Y_i^1 - \frac{\sum_{j\in 0} Y_j^0 G\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{k\in 0} G\left(\frac{p_j - p_i}{h_n}\right)}\right\} \qquad (15)$$

where $G(.)$ is a kernel function and h_n a bandwidth parameter. Both matching methods require the estimation of the propensity score. Any standard probability model can be used for this. In our case we use a logit model, that is:

$$Pr\left(D_{i,owned} = 1 \mid X_i\right) = F\left\{R\left(X_i\right)\right\} \qquad (16)$$

where $F(.)$ is the logistic cumulative distribution and $R(.)$ is a function of covariates with linear and, if necessary, higher order terms.

How can the results of the two approaches be compared? In general we do not expect that the two methods give exactly the same results at least for two reasons. First, different to the control function approach, matching does not require the specification of any response function similar to (7), for this reason matching is usually considered as a non-parametric estimator. In our case, this issue is even more relevant because by the same nature of the dependent variable, discrete or count data methods have to be used, which requires further assumptions in terms of the distribution of the shocks. Second, while the matching method gives an estimation of the "treatment on the treated" effect (that is what the diffusion process of university owned patents would have been in case the were not owned by any university), the control function method gives a estimate of the "average treatment effect", which is the expected effect of treatment on a randomly drawn patent from the population of university based patents. This is true under the assumption that the marginal effects of the probit models are evaluated at the total sample means. An estimate of the treated on the treated effect would require the marginal effects of the probit model be evaluated at the sub sample mean of university owned patents[12].

[12] As we will see in the next section the only two exceptions for this are the linear model for the impact measured on patent values and the negative binomial model for forward citations. In both cases, under the

6. Results

The results coming from estimating the control function using regression techniques are summarised in Table 6. In all the regressions we also add as control a time variable capturing the time elapsed between the patent application and the survey. In this way we can control for the fact that patents have been exposed for different times to diffusion processes. The results regarding the variables of interest are summarised in the first row.

[Table 6 about here]

We see that the treatment effect (university ownership) is positive in terms of the diffusion variables. University-owned patents tend to be used more intensively than non-university owned patents, but only the effect related to licensing is significant. The first column, which combines all three diffusion variables into a single one, shows a 12% increase in commercial use as a result of university ownership (but this is not statistically significant). The effect of the treatment on licensing is 37%.

We also investigate if university owned patent have higher value than the control group or if they were more intensively cited. For these two variables, the treatment effect is in fact negative, but not significantly so (columns 5 and 6).

The results for the remaining control variables are also interesting. First, the country effects tend to be highly significant across all the different specifications and they seem to be more important than the technology effects. This is consistent with the results of a previous study showing an higher relevance of country effects compare to technology effects on the mobility of academic inventors (Crespi, Geuna and Nesta; 2005). Institutional factors play a more important role than technological specificities. For example, in those countries such as the UK where technology transfer offices and their associations (UNICO/AURIL) have existed for longer term we obtained a positive and significant impact on licensing and stat-ups. Similarly, in those countries such as Germany with professorial privilege there was a significantly lower use of patents. Regarding to inventors' background, those inventors with more experience and tenure tend to increase the probability that a given patent is used. Finally, research project with a larger R&D budget tend to increase the value of the expected value of the patent and patent applications involving a large number of IPC field tend to have higher probability of using.

[Table 7 about here]

The results from applying the matching techniques using the nearest neighbour matching method are summarised in Table 7.[13] The results in the table have being generated by using

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assumption that $\beta_1 = \beta_0$, the interaction terms disappear and the "average treatment effect" is similar to the "average treatment on the treated".

[13] We previously verify the balancing property using the procedure by Becker and Ichino (2002): after estimating the logit model to predict the propensity score, we split the sample into (k=5) equally spaced intervals of the propensity score, then within each interval, we test that the average propensity score of the treated and control units does not differ, it the test fails in one interval, we split the interval in half and test again. We continue until, in all intervals, the average propensity score of the treated and the control units does not differ. Within each interval, we test that the means of each characteristics do not differ between treated and control units. If the means of one or more characteristics differ, a less parsimonious specification of the logit is needed. The P-value for the sequence of tests was set to 0.005.

the common support constraint[14]. The results in the third column indicates that 52 controls were selected for the 77 university owned patents in the sample, which means that some control observations were matched more than once to different university owned patents. The remaining columns show the mean differences of both groups in the matched sample, the standard error and the t-test. The results tend to confirm the findings from the regression approach: only in licensing was university ownership statistically significant. The magnitude of the impact was also very similar: 39%. The other impact variables were not significantly different from zero.

[Table 8 about here]

Table 8 shows the results, when using the kernel matching method. The results also correspond to ones with the common support constraint imposed. From the first two columns we can see that for the 77 university owned patents in the sample, we are using all the control patents in the common support region. The results are also very consistent: only licensing is statistically significant with an average impact of 41%.

7. Conclusions

The lack of patenting by universities in Europe has been suggested as a problem behind the so-called European paradox (that Europe is strong in basic science but lags behind in technological applications in world markets). As a result, some have argued that Europe needs legislation that makes university patenting more attractive (like the Bayh-Dole Act in the US). We have provided an in-depth analysis of this issue and conclude that there is no need for such legislation.

First, we find that much of the university research that leads to patents in Europe does not show up in the statistics, because private firms rather than the universities themselves apply for the patent. Hence, there is no statistical record of the university involvement in the patent office records. Thus, the lack of university patents in Europe is really a lack of university-owned patents, not necessarily a lack of university-involved patents.

Second, we have undertaken a statistical analysis of the effects of university ownership on the rate of commercial application (diffusion) of a patent, and on the commercial value of a patent. The analysis controls for the different (ex ante observed) characteristics of university-owned and non-university owned patents, and hence is in accordance with the theory that suggests that university ownership is the endogenous outcome of a bargaining game. Both before and after controlling for such differences between patents, we find no statistically significant effects of university ownership of patents. The only significant (positive) effect that we find is that university-owned patents are more often licensed out, but this does not lead to an overall increase in the rate of commercial use.

Hence we conclude that no additional legislation is needed to make university patenting more attractive in Europe. Whether or not universities own commercially interesting patents resulting from their research, is taken care of by the market, and we find no indication of market failure.

[14] That means the testing of the balancing property and the estimation is performed only on observations whose propensity score belongs to the intersection of the supports of the propensity score of treated and controls. This constraint tends to increase the quality of the matching.

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Table 4. Variable definitions

Block	Variable	Definition
Impact	Patent used	Dummy, 1 if the patent was used commercially in any way (maximum of three dummies below)
	Commercial used	Dummy, 1 if the applicant/owner has used the patent commercially
	Licensed	Dummy, 1 if applicant/owner has licensed out the patent
	Start up	Dummy 1 if the patent was used to start a new firm
	N^o of Forward citations	Number of citations received by the patent
	Expected Value	Value of invention as estimated ex post by inventor, based on interval responses, using mean of intervals (ln)
Inventor Background	Age	Age of the inventor at time of survey
	Graduation	Graduation year of latest degree obtained
	Experience	Number of years between year of graduation and entering the job in which the patent was invented
	Tenure	Number of years in the job when the patent was invented
	Male	Dummy variable for sex
	No univ. degree	Dummy, 1 if inventor has no university degree
	Univ. degree	Dummy, 1 if inventor has a university degree but no postdoc degree
	Postdoc degree	Dummy, 1 if inventor has a postdoc degree
	EPO patent applications	Total number of patent applications at EPO by The inventor (ln)
Invention Background	R&D total costs	Inventor estimate of total R&D costs leading to patent (1000 euro, ln)
	Man Months	Number of man-months for research leading to patent, based on interval responses, using mean of intervals
	Family	Dummy, whether patent is part of a family (a family is a set of technically interrelated patents)
	Scenario	Dummy, 1 if the patent was the result of a targeted effort
	N^o applicants	Number of applicant organizations listed (ln)
	N^o words claim	Number of words in the claims (ln)
	N^o IPC 4 digit	Number of 4 digit IPC classes (ln)
	N^o inventors	Number of inventors listed
	Multiple applicants	Dummy, whether there is more than 1 applicant
Technology Effects	ISI-ElEng	Dummy, 1 for electrical engineering
	ISI_Instr	Dummy, 1 for instruments
	ISI_ChePha	Dummy, 1 for chemicals / pharmaceuticals
	ISI_PrEng	Dummy, 1 for precision engineering
	ISI_MechEng	Dummy, 1 for mechanical engineering
Country Effects	UK	Country dummy United Kingdom
	DE	Country dummy Germany
	IT	Country dummy Italy
	ES	Country dummy Spain
	NL	Country dummy Netherlands
	FR	Country dummy France

Table 5. Patent characteristics in each sub-sample

Block	Variable	Not owned	Owned	std	T	P-value	OBS	Significance
Impact	Patent used (0/1)	0.553	0.688	0.062	-2.180	0.030	433	**
	Commercial used (0/1)	0.473	0.468	0.063	0.092	0.927	433	
	Licensed (0/1)	0.152	0.558	0.049	-8.347	0.000	433	***
	Start up (0/1)	0.084	0.221	0.039	-3.534	0.000	433	***
	N^o of Forward citations	0.500	0.104	0.140	2.836	0.005	433	***
	Expected Value (ln)	5.984	6.131	0.220	-0.668	0.505	433	
Inventor Background	Age	46.5	45.6	1.375	0.610	0.542	433	
	Graduation	1977.8	1978.6	1.380	-0.611	0.542	433	
	Experience	5.397	5.714	0.836	-0.379	0.705	433	
	Tenure	15.014	12.714	1.289	1.784	0.075	433	*
	Male	0.952	0.935	0.028	0.621	0.535	433	
	No univ. degree	0.042	0.052	0.026	-0.380	0.704	433	
	Univ. degree	0.140	0.091	0.043	1.165	0.245	433	
	Postdoc degree	0.817	0.857	0.048	-0.830	0.407	433	
	EPO patent applications	0.633	0.341	0.077	3.784	0.000	433	***
Invention Background	R&D total costs	10.980	11.102	0.219	-0.559	0.577	433	
	Man Months	4.581	5.377	0.222	-3.588	0.000	433	***
	Family	0.493	0.513	0.062	-0.321	0.748	433	
	Scenario	0.483	0.442	0.063	0.661	0.509	433	
	N^o applicants (ln)	0.069	0.124	0.031	-1.758	0.079	433	*
	N^o words claim (ln)	4.765	4.654	0.088	1.267	0.206	433	
	N^o IPC 4 digit (ln)	0.351	0.386	0.056	-0.611	0.541	433	
	N^o inventors	1.097	0.850	0.066	3.735	0.000	433	***
	Multiple applicants (0/1)	0.084	0.156	0.037	-1.928	0.055	433	*
Technology Effects	ISI-EIEng (0/1)	0.143	0.143	0.044	0.009	0.993	433	
	ISI_Instr (0/1)	0.185	0.325	0.051	-2.737	0.006	433	**
	ISI_ChePha (0/1)	0.371	0.286	0.060	1.414	0.158	433	
	ISI_PrEng (0/1)	0.194	0.182	0.050	0.242	0.809	433	
	ISI_MechEng (0/1)	0.107	0.065	0.038	1.111	0.267	433	
Country Effects	UK (0/1)	0.261	0.597	0.057	-5.946	0.000	433	***
	DE (0/1)	0.292	0.052	0.053	4.509	0.000	433	***
	IT (0/1)	0.135	0.026	0.040	2.727	0.007	433	***
	ES (0/1)	0.022	0.117	0.024	-3.927	0.000	433	***
	NL (0/1)	0.132	0.156	0.043	-0.551	0.582	433	
	FR (0/1)	0.157	0.052	0.043	2.437	0.015	433	**

(***) denotes 1% significance level, (**) denotes 5% significance level and (*) denotes 10% significance level.

Table 6. Regression results

	Patent Used	Commercial	Licensing	Start-up	Ln(Value)	Forward Citations
University owned	0.118	0.012	0.372	0.018	-0.186	-0.454
	1.630	0.160	5.64***	0.770	0.790	1.000
UK	-0.104	-0.255	0.277	0.141	0.716	-1.612
	1.390	3.43***	4.13***	3.67***	3.05***	3.67***
DE	-0.325	-0.399	0.094	-0.046	-0.538	0.742
	3.90***	5.13***	1.290	1.280	2.06**	2.29**
NL	-0.350	-0.344	0.051	0.105	-0.196	-1.097
	3.84***	4.11***	0.630	2.00**	0.660	2.07**
ISI_ElEng	-0.210	-0.156	0.072	0.012	0.216	0.133
	1.89*	1.450	0.750	0.300	0.620	0.300
ISI_Instr	-0.046	-0.093	0.094	-0.002	0.101	-0.034
	0.440	0.900	1.060	0.070	0.310	0.090
ISI_ChePha	-0.303	-0.280	0.085	-0.028	0.193	0.157
	2.93***	2.76***	0.980	0.840	0.590	0.370
ISI_PrEng	-0.099	-0.126	0.140	-0.019	-0.281	-0.036
	0.920	1.210	1.460	0.560	0.860	0.080
Age	-0.005	-0.012	0.001	0.000	-0.020	0.029
	0.890	1.95*	0.210	0.000	1.100	1.110
yeardg	0.016	0.013	0.003	0.001	0.018	-0.056
	2.42**	2.04**	0.700	0.580	0.920	1.99**
exp	0.020	0.016	0.004	-0.001	0.033	-0.081
	2.56**	2.06**	0.650	0.250	1.410	2.14**
tenure	0.019	0.019	0.008	-0.001	0.037	-0.072
	2.99***	3.08***	1.74*	0.310	2.03**	2.37**
male	0.084	0.145	0.078		0.632	0.457
	0.650	1.100	0.810		1.640	0.770
Uni Degree	-0.235	-0.212	-0.036	-0.002	0.345	1.527
	1.480	1.450	0.320	0.040	0.730	1.74*
Pos degree	-0.099	0.067	-0.047	-0.036	0.206	1.092
	0.700	0.490	0.430	0.700	0.490	1.280
EPO patent applications (ln)	0.086	0.134	0.005	0.021	-0.143	0.167
	1.79*	2.72***	0.140	1.230	0.970	0.970
R&D total costs (ln)	0.015	0.006	0.010	0.000	0.191	0.039
	0.910	0.380	0.740	0.060	3.59***	0.500
Man Months	-0.012	-0.005	-0.028	0.008	-0.022	-0.068
	0.750	0.280	2.15**	1.370	0.410	0.890
Family (0/1)	0.047	0.053	0.032	0.021	0.152	0.056
	0.870	0.960	0.770	1.070	0.870	0.230
Scenario (0/1)	-0.004	0.004	-0.069	-0.033	0.038	0.414
	0.070	0.070	1.620	1.81*	0.220	1.78*
N° applicants (ln)	-0.115	0.231	0.165	0.230	1.468	0.843
	0.300	0.590	0.590	1.460	1.200	0.620
N° words claim (ln)	0.036	0.043	-0.013	-0.007	-0.021	0.332
	0.910	1.020	0.420	0.500	0.160	1.87*
N° IPC 4 digit (ln)	0.151	0.103	0.086	0.036	0.096	-0.464
	2.48**	1.67*	1.92*	1.86*	0.500	1.540
N° inventors	-0.057	-0.030	-0.066	-0.047	0.103	-0.116

	1.080	0.560	1.67*	2.70***	0.610	0.490
Multiple applicants (0/1)	0.085	-0.277	-0.081	-0.074	-1.148	-0.205
	0.270	0.920	0.410	1.640	1.120	0.170
time	-0.011	-0.017	0.033	-0.001	-0.087	0.217
	0.530	0.820	2.07**	0.200	1.320	2.23**
Observations	433	433	433	433	433	433

Robust t-test in parenthesis. (***) denotes 1% significance level, (**) denotes 5% significance level and (*) denotes 10% significance level. The first 4 columns show the marginal effects of probit model evaluate at sample means. The fifth column shows OLS results and the sixth column shows the negative binomial results.

Table 7. Nearest Neighbour Matching results

n.	treated.	control	ATT	Std. Err.	T
Patent Used	77	52	0.000	0.097	0.000
Commercial App	77	52	-0.097	0.101	-0.967
Licensed	77	52	0.390	0.083	4.693***
Start-up	77	52	0.091	0.077	1.182
Ln(Value)	77	52	-0.325	0.339	-0.958
Fwd_cit	77	52	-0.182	0.102	-1.778**

Note: Analytical standard error.

Table 8. Kernel Matching results

n.	treated.	control	ATT	Std. Err.	T
Patent Used	77	199	0.144	0.083	1.732**
Commercial App	77	199	0.002	0.108	0.015
Licensed	77	199	0.410	0.071	5.791***
Start-up	77	199	0.085	0.066	1.274
Ln(Value)	77	199	-0.332	0.342	-0.968
Fwd_cit	77	199	-0.150	0.083	-1.811**

Note: Gaussian Kernel used. Standard error by bootstrapping with 100 replications.