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

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Abstract
This paper contributes to the current debate on university patents and knowledge transfer at two levels. First we present the results of the comparison of European and US academic patenting systems, and show that the common perception that Europe is lagging behind the US in terms of university patenting is far from being correct. Second, we develop an assessment of the efficiency of the academic IPR ownership model. Specifically, we 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, about two-thirds of the patents that result (at least partly) from university research, are not owned by universities (but instead are owned in large measure by private firms). Given the different importance of Public Research Organisations (PRO) in the 6 EU countries considered, we have done the same analysis also for the case of *PRO-owned* and *PRO-invented* patents. 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.

JEL Subject Classification: O3, I28
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1. Introduction

The role of universities in the production of economically useful knowledge has received much recent attention in the policy debate. Policy initiatives leading to major institutional changes have been carried out in many countries following the idea that the university has to be more proactive in transferring knowledge to industry. It seems to us that in most policy circles, a vision of the 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 in Europe. Specifically, most of the policy attention has focused on the need for European countries to enact a 'Bayh-Dole Act'-like legislation, which is expected to raise the number of patents owned by European universities.

The focus on the role of patenting in knowledge transfer from universities to the private sector seems to largely ignore the empirical evidence that public-private knowledge transfer is a multi-faceted phenomenon that occurs through a number of channels of great variety (e.g., Cohen et al., 1998). These channels include scholarly publications such as journal articles, conferences and workshops where researchers from universities and the private sector meet, employment of graduates in private firms, research joint ventures, consultancy by university faculty, etc. In the setting of such a variegated set of relations and interactions, the model of a university taking out a patent on an invention resulting from one of its basic research projects, and then actively seeking a firm to license the patent to, seems to be only one of the many possible ways of transferring knowledge.

In particular, in the next section, we present evidence that in Europe, even in the context of patented research results, such a characterization of the knowledge transfer process is far from the dominant way found in practice. Our evidence suggests that the largest part of (European) patents in which university researchers are involved as inventors, is owned by private firms, rather than universities. This suggests that the firm is involved in the university research as early as the pre-patent phase, and that who owns the patent (the firm, the university, or, in the context of some European countries, the researcher) is the result of a bargaining process. Our data confirm earlier impressions of the empirical relevance, in Europe, of this type of involvement of university researchers in patenting by firms (e.g., Geuna and Nesta, 2006).

This paper asks the question whether private ownership of patents on university research (or a combination of private and university research) has any effect on the probability of commercialization of the patent, or on the economic value of the patent. We focus on patenting as one channel of knowledge transfer without studying its relative efficiency/effectiveness compared to other channels. Specifically, we compare, in a European context, *university-owned* patents (those patents that have a university assignee) with *university-invented* patents (those patents that have at least one university inventor, but are not owned by the university). 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 issue that emerges from the literature review that we provide below, and which forms the centre of our research question, is whether university ownership of patents on the research that is carried out by its researchers will enhance the efficiency of the knowledge transfer

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

process. The answer to this question obviously has large policy implications, because, as we show below in Section 3, many European universities tend to leave their patents to be owned by private parties (mostly firms).

The literature review suggests that there may indeed be effects of patent ownership on the economic efficiency of patenting as a channel of university-to-private knowledge transfer. In particular, it is suggested (Agion and Tirole, 1994) that private ownership of patents in which university researchers cooperate may lower their incentive to provide a high-quality contribution, and (Hellman, 2005) that private ownership may be associated to less-efficient searching for commercial partners from the side of the university of the individual researcher. Our theoretical review also briefly covers the issue of what influences the decision of university researchers to yield the patent to the university or a private firm (Jensen, Thursby and Thursby, 2006).

The paper is organised as follows. In Section 2 we review the relevant theoretical contributions of IPR ownership in the context of public-private research joint ventures and present our hypotheses. The data sources and descriptive statistics on university patent ownership are presented in the Section 3. Section 4 introduces further explanatory variables that we will use in the statistical analysis, and presents descriptive statistics of these. Section 5 introduces the methodology and presents estimation 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', policy emphasis has been put on the working of industry – science relations in Europe. The suggestion is that these relations leave much to be desired, and that policies are needed to make them more efficient.

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 institutions, 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 using 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. Mazzoleni (2005) analyses the social

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

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, it is less relevant for the focus of our research, below we briefly discuss the predictions of the Hellman and Agion and Tirole models.

The Hellman model is primarily aimed at the questions whether patents are an efficient form of knowledge transfer, and hence does not primarily focus on the issue of patent ownership. However, we feel that this model still has strong implications for our research question. It considers a two-stage research process, in which a university researcher (the 'scientist') first develops an 'idea', and then seeks a firm to develop this idea into a commercial project. The main question that the model addresses is whether it makes any difference for the search process whether or not the idea is patented. Hellman shows that patents increase the incentive of the scientist to invest in search, but that the incentive of the firm to search for scientists is lowered by the patent (because the patent strengthens the bargaining power of the university/researcher).

In an elaborate version of the model, there are three parties involved in the matching process: the scientist, the university (represented by a Technology Transfer Office, TTO), and the firm. In this model setup, the assumption is that the TTO has lower search costs, compared to the scientist, when looking for interested firms. For a given cost expenditure, the TTO realizes a higher probability for a match than the scientist on her own does. Hence the involvement of the TTO increases the efficiency of the commercialization process, and also the expected rate of commercialization of university research projects. Hellman *assumes* that if the idea is patented, the patent is owned by the university, and the TTO is involved. This implies that once the idea is patented, the scientist looses control over it: negotiations on licensing etc. take place between the TTO and the firm. The scientist does have a choice, however, of whether or not disclosing the invention (to the TTO). The advantage of disclosure is that it raises the search efficiency, and hence the probability of commercial application. In return for this probability, the scientist can negotiate an up-front fee, or a share of the licensing income, from the TTO.

The disadvantage of disclosure is that the scientist is no longer in a position to negotiate directly to the firm, because the TTO owns the patent. The firm, the TTO and the scientist are involved in a three-party bargaining game, and the relative share that the scientist gets from this game is lower than in the case of a direct bargaining process with the firm, in the version of the model where the TTO does not exist. Thus, the scientist faces a trade-off between disclosing, which raises the probability of commercialization, but lowers the pay-off of it, and non-disclosure, which lowers the probability of commercialization but raises the pay-off of it.

Hellman shows that there are (plausible) parameter values where the negative effects of disclosure outweigh the positive effects, as seen from the scientist's perspective. In this case, which is particularly likely when the search costs advantage of the TTO is not particularly strong (e.g., when the scientist is strongly embedded in a network with private firms), the scientist may choose not to disclose the idea to the TTO, but instead to search herself for an interested firm and 'sell' the idea directly to this firm. Note, however, that in Hellman's model, "the major drawback is that without disclosure, the scientist never wants to file a patent, since the university would simply lay a claim on it" (Hellman, 2005, p. 26). It seems consistent to assume that in such cases, the firm would still patent the idea, and hence the firm patent would turn up with a university inventor.

Although Hellman (2005) does not undertake a detailed welfare analysis of the case, it is clear that there may be a negative impact on social value of the university research if the scientist decides to not disclose the invention. This results, for example, because the involvement of the TTO, through its lower search costs, will increase the probability of commercialization. Thus, we conclude that in the setting of the Hellman model, private ownership of patents based (partly) on university research, may be an indication of a less efficient matching process, and hence may lower the probability of commercial application of the patent.

The paper by Aghion and Tirole (1994) analyzes the issue of the ownership of the patent in a different setting, which is the case of joint research projects between universities and private firms. They conclude that the assignment of property rights (patents) to the firm rather than the university may lead to market failure, i.e., the innovation resulting from the collaboration will have a lower value than could have been the case if the university had owned the patent. In this model, a university undertakes a research project for a private firm. Both parties need to invest in the project. Due to 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.

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 of 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 bargaining 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) $\mathbf{V^0}$. 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, $\sigma(\mathbf{V^0} + \Delta) < \mathbf{V^0}$, or $\Delta < \mathbf{V^0}(1 - \sigma)/\sigma$ would be sufficient to prevent 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. 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 is not 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 in which the university owns the patent (i.e., 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.

In the context of our empirical analysis below, the question what determines whether a patent on university research is owned by the university, plays an essential role. Obviously, both the Hellman (2005) and Aghion and Tirole (1994) models address this issue. In Hellman (2005), it is the relative efficiency of the university researcher in searching for interested commercial parties, as well as the value of involving the university researcher in the development process (this increases the bargaining power of the scientist) that are the main input into the decision on disclosure of the patent. In Aghion and Tirole (1994), it is primarily the relative (marginal) contribution of the university researcher to the research outcome that influences ownership.

Finally, the recent paper by Jensen, Thursby and Thursby (2006) addresses the issue of patent ownership in a more direct way. Their model is a 2-stage game, in which a research project is first applied for funding with public funding agencies, and in a final stage may be commercialized by consulting of the university scientist to a firm. Their model focuses on the impact of differences in the quality of the university researcher, and differences in the difficulty of the research project. With higher quality researchers, the model predicts that university ownership of the resulting patents is more likely (ceteris paribus). Project difficulty mainly works indirectly through research agency funding, and the effect of more funding is argued to increase the likelihood of university ownership.

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 it 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 (see also our above discussion of Hellman, 2005). 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 the 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 the share of research directly funded by large independent funding organizations is still relatively small (possibly with the exception of the UK). 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 to solve the "European paradox". The evidence usually put forward is that European universities have many fewer patents than US universities and there is therefore a 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 88% of granted EPO patents whose first inventor has an address in of the EU-15 countries (about 42% of the total EPO). 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 considered 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. Gambardella, Harhoff and Verspagen (2005) have constructed sampling weights for the 9,017 observations, defined as the inverse probability of a patent being in the set of 9,017 observations. These weights are based on a comparison of the responses with all granted patents with a similar priority date in the six countries, on the basis of observable characteristics in the patent document (such as inventor country, priority date, technology class), as well as citations received. These weights enable us to assess the representativeness of the 433 university patents relative to the total sample, i.e., to determine whether or not the inventors of university patents are more or less likely to respond.

The results of this calculation show that we have a very small overrepresentation of university patents: the share of our 433 cases in the sum of the sampling weights over the complete (n = 9,017) sample is 4.93%, while in terms of the number of observations, their share is 4.80% (433/9,017).[3] In the remainder of this paper, we ignore this, and proceed as if our university patents sample is representative of the larger universe in the six countries.

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.[4] In all countries except Spain, the fraction of *university-owned* patents in *university patents* is far below half.

Table 1. Ownership of European *University/PRO Patents*

	Germany	Italy	France	UK	Spain	Nether-lands	Total
Number of *University patents*	108	50	60	139	17	59	433
University-owned patents	4	2	7	45	9	12	79
	4%	4%	12%	32%	53%	20%	18%
University-invented patents	104	48	53	94	8	47	354
	96%	96%	88%	68%	47%	80%	82%
Number of *PRO patents*	62	13	77	37	7	40	236
PRO-owned patents	45	4	24	0	4	23	100
	73%	31%	31%		57%	57.5%	42%
PRO-invented patents	17	9	53	37	3	17	136
	17%	69%	69%	100%	43%	42.5%	58%

Although this paper focuses mainly on academic patents, the intricacies of the university system in certain EU countries such as France and Italy, for example, in which Public Research Organisations (PROs) overlap at least in part with universities, requires us also to consider *PRO-patents* (those patents that have at least one PRO inventor). The second part of Table 1 provides this information. As expected, countries with important PRO infrastructure such as France and the Netherlands have a significant number of number of *PRO patents*, less so the UK where most of the research is carried out in universities. France is the only country where the number of PRO patents in the sample is larger than the number of university patents.

Interestingly, compared to the situation in universities, the case of *PRO patents* is less clear-cut in terms of ownership. Although in the data for all countries the number of *invented* PRO patents is still the majority, this is the result of opposite situations in the various countries (probably dependent on different institutional and legal configuration). In the cases of

[3] These results differ between countries. The shares of university patents in the samples per country are as follows (the results are presented as share in number of cases/share in weights): UK 9.01%/9.22%, DE 3.23%/3.62%, FR 4.04%/3.95, IT 4.00%/3.94%, NL 5.25%/5.18%, ES 6.32%/6.07%. The deviation between the two percentages is most serious in Germany (DE), where we seem to have some overrepresentation of university inventions.

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

Germany, the Netherlands and Spain *PRO-owned* patents are more frequent than *PRO-invented* patents, the contrary applies to the cases of France, Italy and the UK.[5]

Table 2 analyses in more detail the ownership structure of *invented* patents. About 4/5th of the *university-invented* patents are owned by companies, 10% are assigned to governmental offices of various kinds, PROs and other Public Private Partnerships (PPPs) and 9% to individuals (mostly in the case of Germany and Italy).[6] Companies play a (slightly) less dominant role in the case of *PRO-invented* patents, accounting for about 60% of them. Apparently, PROs being more often more directly linked to government results in a higher share of ownership by governmental offices (about 30%). A particular case is military research, 17% of the *PRO-invented* patents where assigned to the UK Secretary of State for Defence (UK), underlying the important role of military research in the UK. Finally, individuals account for 9% as in the case of university patents.

Table 2. Ownership of European *University/PRO Invented Patents*

	Ownership	Total Sample
University-invented patents	Companies	287 (81%)
	Government, PRO, PPP	36 (10%)
	Individuals	31 (9%)
PRO-invented patents	Companies	81 (60%)
	Government, Univ., PPP	43(31%)
	Individuals	12 (9%)

The first 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), as often claimed by most policy literature. Some commentators have argued that Europe is 20 years behind the US, referring to the Bayh-Dole Act 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 USPTO patents depending if we considered all USPTO patents or only the one assigned to US organisations (private and non-profit) (NSF, 2004). Given the absence of a response bias for university patents, it is clear that European universities have a (broadly) similar share as compared to US universities. Why do our results differ in such a dramatic way compared to the commonly accepted policy view of a technologically low-performing higher education system in Europe? The most important

[5] The case of the UK can be explained by the fact that the only two major PROs were active in the period considered. These were DERA (now privatised as QuinetiQ) and the Medical Research Centre, both owned by the respective ministry and therefore the ownership of patents was assigned to the ministries.

[6] In the period considered in our analysis, the British Technology Group (BTG) was created from the privatisation of the National Research Development Corporation (merged with the National Enterprise Board), the public organisation created in the late 1940s to commercialise innovations resulting from publicly funded research. Following the tradition, until the mid 1990s, BTG was chosen by a large number of universities to be the assignee of academic patents. Our sample includes 14 patents assigned to BTG, they were classified in the companies class.

reason is that official data take only into account *university-owned* patents, and therefore underestimate in a macroscopic way the activity of European universities. Thursby, Thursby and Fuller (2006) show that this phenomenon (firms owning patents to university research) also occurs in the (post Bayh-Dole) US, although at a relatively lower frequency than in the European sample we use.

Table 3. Ownership of US University Patents

	Share of total academic patents
Total number of *University patents*	5772
# *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).

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, Thursby, Thursby and Fuller (2006)[7] have put together information at the inventor level controlling for ownership for 87 research intensive universities accounting for about 5,800 patents in the middle 1990s. Table 3 presents an elaboration of their data.

Although we acknowledge that the two samples may be not perfectly comparable, the first striking observation that can be is that while in the US about 2/3rd of *university patents* are owned by the university that employed one of the inventors, in Europe university ownerships accounts for less than 1/5th. These data seems to point to the existence of two different models 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). Instead, the European model of academic technology transfer is mainly based on a direct transfer of property rights from the academic inventor (or university) to the private sector (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 Act had in the US system. But does this lead to a much higher academic patents production in the US system as compared to Europe? If we adjust the data for the US taking into account that the official statistics underestimate of about 1/3rd the number of *university patents* (generalising the result of Table 3 that about 1/3rd 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% (depending on whether US university patents are expressed as a share of total USPTO-issued patents, or only those assigned to US residents). Anecdotal evidence suggests that the share of foreign-residents in holding domestic patents is higher in the US than in Europe, and hence the upper end of the bracket (5.7%) is probably a better benchmark than the lower bracket. Comparing the upper bracket value with the 4.8% from our sample, we conclude that US academic patent output as a fraction of total patents is at most about 15% higher in the US than in Europe.

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

To understand the relative importance of this difference it is worth remembering (Table 2 above) that a significant part of the European science system is institutionally organised in the various national public research organisations (such as the Max Plank Institute, CNRS, CNR, etc..) while public research organisations in the US tend to be more specialised and have a relatively lower size. Thus, a sizable portion of European scientific activity that generates patents is situated outside the university system in the public research organisations (Cesaroni and Piccaluga, 2005), therefore some of the difference between US and European academic patent output should be attributed to the different institutional set up.

These back-of-the-envelop calculations aim to make the point that once the available data is adjusted for the ownership structure, thus taking into account the different university technology transfer models, and for the different institutional set up of science, it is not so clear that the US system is outperforming the European system. US universities may have had more patents than European universities in absolute terms, however they did not have a much higher share of national patents.

These results shed some doubts on the impact that the Bayh-Dole Act has had on the US academic system and on the value of its applicability to the European context. Our data seems to be consistent with the evidence put forward by a series of papers of Mowery, Nelson, Sampat and Ziedonis[8] that argued that the increased number of university patents is mainly due to the emergence of the new technological opportunities offered by biomedical and ICT research as well as the changes in IPR regulation carried out in the US during the eighties and nineties to increase appropriability and patentability. 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 shown by the increased number of *university patents* in the 1980s' and 1990s'.

3.1 Technology transfer and market failure

Apparently, although European universities are involved in research with commercial value (i.e., leading to patentable inventions), they do not particularly care to exploit the results of this research by means of owning the associated patent. As the review of the Aghion and Tirole model above suggests, either 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 4 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 4. 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% are *university-owned*. Within the group of patents with only university inventors, this percentage is larger (31%), although still clearly less than half. Thus, if we take the distribution of inventors over the

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

research partners as a (broad) indication of relative marginal research impact, the data seem to support the idea (in Aghion and Tirole) 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 also have data on the (perceived) value of inventions,[9] 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. Explanatory variables and descriptive statistics

There are 433 university related inventions in the PatVal dataset, 79 (18%) of them owned by the university and 354 (82%) owned by a firm or another non-university entity. We start by studying the characteristics of the university-owned and non-university-owned sub samples along a list of variables capturing both invention and inventor's backgrounds. Table 5 presents the variable definitions.

We have constructed six variables to try to capture the economic value and the rate of commercial application of patented inventions.[10] Three of these capture the commercialization of the patent: commercial use by the applicant itself, licensing[11] and creation of a start up. These three variables are dummy variables with value 1 if the respondent indicated patent use. We also construct a summary variable *Patent Used* with value 1 if at least one of the three forms of use had value 1. The PatVal Questionnaire also asked the respondent to provide a (subjective) evaluation of the value of the patent. The responses were structured in 10 asymmetric intervals ranging from less than €30,000 to more than €300 million.[12] Finally we used the number of forward citations as a proxy for the use of the patent in subsequent inventive processes. Finally, we include the number of citations

[9] For discussion on the robustness and use of the information on the (perceived) value of invention see Gambardella et al. (2005).
[10] See Appendix 1 for a selection of questions used in the PatVal questionnaire regarding this category of variables.
[11] We assume that if a patent is licensed, the licensee commercializes the patent.
[12] Although this is a subjective variable that could be severely contaminated by measurement errors, it has been extensively validated by the PatVal team and the results of this validation process seemed highly consistent (see Gambardella, et. al, 2005, Giuri, Mariani, et al., 2005).

received by a patent (forward citations), which has been proposed by, among others, Trajtenberg (1990) as an indirect indicator of economic value of the patent.

Table 5. 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° 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. We took the natural log of the mean value of each interval plus the right border of the lowest interval and the left border of the top interval.
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
	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)
	N° words claim	Number of words in the claims (ln)
	N° IPC 4 digit	Number of 4 digit IPC classes (ln)
	N° inventors	Number of inventors listed
	Multiple applicants	Dummy, whether there is more than 1 applicant
	Cooperation	Dummy, whether non-university inventor(s) were present
	FormCol	Dummy, whether there was a formal collaboration agreement
Technology Effects	ISI-EIEng	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

To control for heterogeneity between patents, we built 16 control variables capturing inventor background –a set of variables with background information of the inventor answering the questionnaire[13]– and invention background –a set of variables with information about characteristics of the invention process leading to the patent. Finally, to control for institutional characteristics such as differences in the legal system and technological opportunities, we created country –according to where the research leading to the invention was located– and technology dummy variables –according to the patent's main IPC at 4 digits. Table 6 presents a comparison of these variables according to the ownership of the patent (*university-owned* versus *university-invented*).

Table 6. Patent characteristics in each sub-sample

Block	Variable	University Owned	University Invented	Std	T	P-value	OBS	Significance
Impact	Patent used (0/1)	0.709	0.548	0.061	-2.632	0.009	433	***
	Commercial used (0/1)	0.494	0.468	0.062	-0.421	0.674	433	
	Licensed (0/1)	0.557	0.150	0.048	-8.456	0.000	433	***
	Start up (0/1)	0.228	0.082	0.038	-3.825	0.000	433	***
	N° of Forward citations	0.114	0.500	0.138	2.792	0.006	433	***
	Value (ln)	6.226	5.962	0.218	-1.212	0.226	433	
Inventor Background	Age	45.6	46.5	1.361	0.691	0.490	433	
	Graduation	1978.9	1977.7	1.366	-0.936	0.350	433	
	Experience	5.722	5.394	0.828	-0.395	0.693	433	
	Tenure	12.418	15.093	1.275	2.099	0.036	433	**
	Male	0.937	0.952	0.027	0.558	0.577	433	
	Postdoc degree	0.899	0.808	0.047	-1.923	0.055	433	*
	EPO patent applications	0.290	0.646	0.076	4.709	0.000	433	***
Invention Background	R&D total costs	11.181	10.961	0.216	-1.017	0.310	433	
	Man Months	5.411	4.569	0.219	-3.847	0.000	433	***
	Family	0.468	0.503	0.062	0.560	0.576	433	
	N° words claim (ln)	4.682	4.758	0.087	0.873	0.383	433	
	N° IPC 4 digit (ln)	0.419	0.343	0.056	-1.353	0.177	433	
	N° inventors	0.869	1.094	0.066	3.436	0.001	433	***
	Multiple applicants (0/1)	0.152	0.085	0.037	-1.826	0.069	433	*
	Cooperation (0/1)	0.152	0.565	0.059	6.991	0.000	433	***
	FormCol (0/1)	0.380	0.723	0.057	6.057	0.000	433	***
Technology Effects	ISI-EIEng (0/1)	0.165	0.138	0.044	-0.599	0.550	433	
	ISI_Instr (0/1)	0.291	0.192	0.051	-1.958	0.051	433	*
	ISI_ChePha (0/1)	0.304	0.367	0.596	1.064	0.288	433	
	ISI_PrEng (0/1)	0.177	0.195	0.049	0.361	0.718	433	
	ISI_MechEng (0/1)	0.063	0.107	0.037	1.183	0.238	433	
Country Effects	UK (0/1)	0.570	0.266	0.056	-5.396	0.000	433	***
	DE (0/1)	0.051	0.294	0.053	4.612	0.000	433	***
	IT (0/1)	0.025	0.136	0.040	2.792	0.006	433	***
	ES (0/1)	0.114	0.023	0.024	-3.834	0.000	433	***
	NL (0/1)	0.152	0.133	0.043	-0.447	0.655	433	
	FR (0/1)	0.089	0.150	0.043	1.422	0.156	433	

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

[13] Note that the inventor who answered the questionnaire is not necessarily always (one of) the university inventors of the patent.

The country effects show that there are major differences between both sub samples in the distribution of patents across the different countries, in line with the results presented above in Table 1. The UK and Spain account for a significantly higher fraction of patents in the university-owned group than in the university-invented group, while in Italy and Germany, the situation is reverse. For France and the Netherlands, we do not reject the null hypothesis of a balanced proportion of both types of patents.

In comparison to the major differences in the distribution of the rates of university-owned patents across countries, the results regarding the technology effects are more balanced. Indeed, the only technology class where we are able to reject the null hypothesis of equal shares in both groups is Instruments, with 29% of university owned patents but only 19% of patents in the other group. But this difference is only significant at the 10% level.

Regarding the differences in the distribution of inventor's characteristics across both sub samples of patents, we also observe a fairly balanced pattern. The only exceptions are the variables Tenure and the number of EPO patent applications by the inventor, where the mean is higher in the non-university owned group, and whether or not the inventor holds a postdoc (PhD) degree. Non-university owned patents have a (much) higher fraction of inventors with a postdoc degree.

There are more statistically significant differences regarding to some of the characteristics of the invention process. Here we find that the mean number of man months invested in the invention process is higher in the case of university owned patents (although we do not find a significant variable for the financial investment, i.e., R&D costs). The proportion of patents with multiple applicants is also higher in the university owned patents. On the other hand, the number of inventors per patent is higher in the non-university owned group of patents. Finally, we find that the proportion of patents in which there was cooperation (meaning that both university- and non-university-inventors were present) is higher for the non-university-owned group, and the same holds for patents wre the respondent reported a formal collaboration.

Finally, and most directly related to our research question, for the variables on commercialization and value, we do not find any difference between the two groups with regard to the inventor's perceived value of the patent. On the other hand, we do find that the number of forward citations is higher in the non-university owned group. However, the probability of that the patent was actually used is higher in the group of university owned patents. Investigating further the reasons for this higher rate of used by university owned we find that this is related to two effects: licensing (56% of university owned patents were licensed with only 15% in the other group) and launching start up firms (23% of university owned patents were also used as a basis for starting-up a new firm versus 8% only in the other group). Perhaps surprisingly, we find no significant difference between the two groups with regard to commercial application by the applicant itself. Since universities are normally not in the habit of undertaking economic activity other than education and research, we would expect that this variable would be rather low for the university category. However, we find that roughly half of the university owned patents are reported to have been used for commercial purposes by the applicant/owner. Our suspicion, based on inspection of the data, is that (university) respondents have taken licensing as one form of commercial application, and hence this variable overlaps partly with the licensing variable. This implies that we should not put too much emphasis on the results for this particular variable, and instead focus mainly on the other use variables, including (especially) the one that summarizes the various categories (*Patent Used*).

5. Statistical Results

Taking these differences (or the absence of them) in the rate of commercialization and the value variables at face value, we cannot determine whether they are related to the ownership effect, or to some other underlying differences between the patents in each of the two samples. In other words, are the findings for commercialization and value due to university ownership, or to other heterogeneity between the two samples? Possibly, the observed heterogeneity between the two samples might even be causally related to the ownership value (this is what, e.g., the Aghion and Tirole model assumes), which further complicates drawing inference on the effects of university ownership.

We approach this problem by two separate statistical techniques, both explained in more detail in Appendix 2. The first of these estimates a regression explaining in turn each of the commercialization and value variables. The explanatory variables include a wide range of possible factors influencing the commercialization or value, and this list includes the university ownership value. In this way, we hope to disentangle the various influences on commercialization and value, so that we can identify the university ownership effect separately.

The second technique that we apply starts from identifying the university owned patents as a sample of so-called 'treated' patents (the 'treatment' is university ownership). It then proceeds by constructing a control sample of 'non-treated' (*university invented*) patents. The point is that the control group should be as similar as possible to the treated sample in all ways, except, of course, the treatment (university ownership). Given the adequacy of such a control group, we can apply a *t*-test for differences in the means of the commercialization and value variables to test our research hypotheses.

The way in which we construct our control group is a two-stage process (Rosenbaum and Rubin, 1983). This starts by estimating a (logit) regression for the treatment (ownership) variable. This regression is aimed at explaining which patents are university owned, and hence the predicted values from this provide an estimated probability that a particular patent will be university owned. We then, in the second stage, construct the control sample by drawing for each treated patent a control that has a probability score that is as close as possible to the treated patent.

5.1. Control function regressions

The results from estimating the control function using are summarised in Table 7. 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 to diffusion processes for different times. Given the different scaling of the variables, we apply a range of regression models. In the first four columns, which are all dealing with binary dummy variables, we use a probit model. In the regression for value, we apply a simple OLS model, and in the model for citations, we use a negative binomial model. Obviously, the nature of the estimated coefficients varies between those models.

Table 7. Regression results

	Patent used	Commercial used	Licensed	Start up	Value (ln)	Forward citations
University owned	0.146	0.063	0.353	0.034	-0.21	-0.389
	(1.99**)	(0.78)	(5.44***)	(1.28)	(0.95)	(0.91)
ES	-0.299	-0.156	-0.126	-0.042	0.161	1.506
	(2.13**)	(1.10)	(1.85*)	(1.21)	(0.37)	(2.16**)
DE	-0.154	-0.103	-0.100	-0.096	-1.274	2.607
	(2.05**)	(1.30)	(2.10**)	(3.10***)	(5.62***)	(6.41***)
NL	-0.211	-0.079	-0.141	-0.013	-0.819	0.583
	(2.48**)	(0.92)	(3.04***)	(0.54)	(3.16***)	(1.02)
FR	0.416	0.564	-0.204		-0.99	1.252
	(4.48***)	(5.80***)	(4.60***)		(3.79***)	(2.66***)
IT	-0.259	-0.076	-0.14	-0.029	-0.432	1.979
	(2.24**)	(0.79)	(2.51**)	(1.11)	(1.52)	(4.42***)
ISI_ElEng	-0.256	-0.204	0.078	0.059	0.175	0.443
	(2.23**)	(1.83*)	(0.82)	(1.16)	(0.53)	(0.98)
ISI_Instr	-0.117	-0.165	0.121	0.023	0.098	0.21
	(1.11)	(1.57)	(1.35)	(0.55)	(0.32)	(0.54)
ISI_ChePha	-0.397	-0.381	0.085	-0.012	0.208	0.226
	(4.05***)	(3.89***)	(1.05)	(0.32)	(0.72)	(0.57)
ISI_PrEng	-0.176	-0.214	0.157	-0.018	-0.252	0.074
	(1.62)	(2.01**)	(1.68*)	(0.46)	(0.81)	(0.18)
Age		-0.012				
		(2.08**)				
Graduation	0.019	0.015				-0.018
	(3.04***)	(2.33**)				(1.73*)
Experience	0.018	0.019				
	(2.41**)	(2.21**)				
Tenure	0.016	0.02	0.006			
	(2.70***)	(2.96***)	(3.28***)			
Postdoc degree	-0.192					
	(2.19**)					
EPO patent appl.	0.112	0.167				
	(2.26**)	(3.15***)				
R&D total costs					0.191	
					(4.08***)	
Man Months			-0.032			
			(2.81***)			
Family	0.124	0.129		0.043		
	(2.27**)	(2.23**)		(2.13**)		
N^{o} words claim (ln)						0.367
						(2.11**)
N^{o} IPC 4 digit (ln)	0.146	0.108	0.076	0.050		
	(2.39**)	(1.69*)	(1.75*)	(2.33**)		
N^{o} inventors				-0.048		
				(2.47**)		
Multiple applicants		-0.193		-0.051		
		(1.89*)		(1.83*)		
Cooperation (0/1)	-0.125	-0.117	-0.122			
	(2.14**)	(1.87*)	(2.78***)			
FormCol (0/1)				-0.064		
				(2.65***)		
Time			0.029		-0.123	0.23
			(1.93*)		(1.95*)	(2.38**)
Constant					5.411	29.701
					(7.75***)	(1.43)
Observations	433	433	433	433	433	433
(Pseudo) R^2					0.14	0.14

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.

In all cases, we started by estimating a 'full model' that includes all variables on inventor background, invention background, and technology and country effects, as the explanatory variables. We reduced this model to a more parsimonious model by excluding, one-by-one all variables that were not significant at the 10% level or better. Country dummies, technology dummies and the commercialization and value variables were never removed from the regression, independent of their significance level.

With regard to the treatment variable (university ownership), we observe that this is significant for *Patent Used* (overall rate of commercialization) and licensing. It is not significant for the other variables, including both measures of value.[14] Thus, our finding here indicates that, overall, university-owned patents tend to be 15% more often used than non-university owned patents. Of the individual categories that make up overall commercialization, only the effect of licensing is significant (35% more often). For value and citations, the treatment effect is in fact negative, but not significantly so (last two columns).

The results for the remaining control variables are also interesting to briefly inspect. First, the country effects tend to be highly significant across all columns 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). The UK, where technology transfer offices and their associations (UNICO/AURIL) have existed longer, is the reference country (its dummy has been excluded from the estimations), and the generally negative signs for the other countries in the first four columns indicate that commercialization is relatively high in the UK.

Country-level institutional factors play a more important role than technological specificities. Of the technology effects, only few are significant, and these seem to point out that in electrical engineering and chemicals and pharmaceuticals, commercialization is less frequent.

Regarding inventors' background, we find that experience (in general terms) contributes positively to the rate of commercialization. The variables Graduation, Experience, Tenure, and the number of EPO patent applications all show up with positive and significant coefficients in at least two equations. Age and having a postdoc degree, on the other hand, have a significant negative impact in one equation. None of the variables in the inventors characteristics block, however, has a very robust influence on the two value indicators.

This is similar in the project characteristics block. Here, we find that economic value, in our approach is only explained by the R&D budget (and country effects).[15] The number of words in the claims of the patent explains the number of forward citations. The other variables have an influence on the commercialization indicators. Interestingly, larger projects (in terms of man months) show a lower rate of licensing. Whether or not a patent is part of a larger set of interrelated patents (family) affects commercialization positively, and so does the number of IPC classes that apply to the patent. The number of inventors, the number of applicants, and the two collaboration variables affect commercialization negatively.

5.2. Treatment effects and matching

The first stage of the treatment effect method is the estimation of the probit equation that predicts university ownership. We use the familiar set of regressors in this equation. The

[14] The signs and significance levels of the university ownership variable is always identical between the full model and the parsimonious model, and hence our conclusions are not affected by including or excluding explanatory variables.

[15] Gambardella, Harhoff and Verspagen (21005) provide a more elaborate approach to explaining patent value than we can offer here, and provide more enlightening insights for the total PatVal sample.

inventor-related variables are assumed to be a good proxy of the variables that Jensen, Thursby and Thursby (2006) rank under "researcher quality", but note that our inventors are not necessarily always the university inventors. Still, we can take the observed inventor characteristics as representative of the set of all inventors of the patent. We would expect that an increase in the quality of the inventor raises the probability that the patent is assigned to the university. We do not have the same variables on public funding as Jensen, Thursby and Thursby (2006) apply, but the variables in our project characteristics block do give us an indication of the complexity of the project, and this captures the same tendency that Jensen, Thursby and Thursby capture through their funding variable. We would expect that in general, for "more difficult" projects, the likelihood of university ownership increases. This is also in line with Aghion and Tirole, since in this case the marginal university contribution should assumed to be higher.

We also apply the same process of eliminating insignificant variables from the equation. The only change we make in this respect is that we only accept final specifications that satisfy the balancing restriction (this is a test of whether for a given propensity score, treated and control observations are on average observationally identical, see the Appendix 2 for technical details).[16] The results of these p-score regressions are documented in Table 8. [17]

We apply three different samples, corresponding to the three columns in the table. The first columns gives estimations for the complete sample (433 cases). Here, we find that inventors with recent diplomas (negative sign on Graduation), less time in the current job (negative sign on Tenure), with less experience in previous patenting (negative sign on number of EPO patents), or of a higher age (positive sign on Age) tend to have a higher probability of assigning the patent to the university. This is somewhat contrary to the findings in Jensen, Thursby and Thursby (2006), who argue that higher quality inventors are more likely to assign to universities. To the extent that experience is an indicator of quality, our results at least partially contradict this expectation, suggesting that additional theoretical work on this issue for Europe might provide valuable insights.

[16] If the balancing property is not satisfied, we include the last insignificant variable that we excluded, until the restriction is satisfied.

[17] We 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, as described in the main text. The P-value for the sequence of tests was set to 0.005.

Table 8. P-score regression results (logit estimation)

	Sample 1	Sample 2	Sample 3
ES	0.816	0.313	1.071
	(1.12)	(0.43)	(1.29)
DE	-3.647	-4.300	-3.414
	(4.81***)	(5.33***)	(3.84***)
NL	-1.187	-1.757	-1.602
	(2.40**)	(3.30***)	(2.91***)
FR	-2.294	-3.045	-2.137
	(3.91***)	(4.74***)	(3.17***)
IT	-2.279	-1.9	-2.152
	(2.70***)	(1.98**)	(2.24**)
ISI_ElEng	1.416	1.628	2.203
	(1.83*)	(1.96**)	(2.45**)
ISI_Instr	1.226	1.551	1.939
	(1.72*)	(2.05**)	(2.37**)
ISI_ChePha	0.969	1.709	2.022
	(1.37)	(2.16**)	(2.32**)
ISI_PrEng	1.538	1.983	2.403
	(2.00**)	(2.40**)	(2.66***)
Age	0.085	0.108	0.108
	(2.47**)	(3.34***)	(3.00***)
Graduation	-0.063		
	(1.38)		
Experience	-0.166	-0.129	-0.146
	(3.12***)	(3.25***)	(3.34***)
Tenure	-0.171	-0.137	-0.137
	(3.72***)	(4.04***)	(3.62***)
Male		-1.278	
		(1.69*)	
Postdoc degree		1.205	
		(1.68*)	
EPO patent appl.	-1.592	-1.527	-1.782
	(3.92***)	(3.63***)	(4.06***)
Man Months	0.183	0.179	0.298
	(1.91*)	(1.81*)	(2.66***)
Family	0.519		0.714
	(1.40)		(1.64)
Nº words claim (ln)		0.563	0.53
		(2.03**)	(1.74*)
Nº inventors			-0.547
			(1.41)
Multiple applicants	1.967	2.121	2.7
	(3.62***)	(3.69***)	(4.11***)
Cooperation	-2.048	-2.155	-2.089
	(4.61***)	(4.63***)	(4.05***)
FormalCol	-0.975	-1.038	-1.701
	(2.78***)	(2.83***)	(4.20***)
Constant	123.274	-5.738	-6.029
	(1.34)	(2.87***)	(2.85***)
Observations	433	421	366

Robust t-test in parenthesis. (***) denotes 1% significance level, (**) denotes 5% significance level and (*) denotes 10% significance level. Sample 1 is the complete sample, Sample 2 excludes from this 12 patents assigned to the Department of Defence in the UK, Sample 3 compares all university-owned patents only with patents owned by firms (in the latter case, patents held by BTG in the UK are treated as firm patents).

In the project characteristics block, the presence of multiple applicants and the project size (man months) raises the probability of university ownership, which is consistent with our above theoretical expectations. The presence of non-university inventors (Cooperation) or the existence of a formal collaboration (FormalCol) decreases it. The country dummies are negative with the exception of Spain (the UK is the reference country), while the technology dummies for electrical engineering, instruments and precision engineering are positive and weakly significant (mechanical engineering is the reference technology).

In the second column of Table 8, we exclude 12 patents assigned to the UK Department of Defence. None of these patents score a 1 on any of the commercialization variables, and they might therefore bias the results in favour of finding a positive effect of university ownership. In the third column, we exclude all patents that are not owned by a firm or a university, so that this sample compares university-owned patents only to firms owned patents. Thus, this sample excludes patents that have been assigned to individuals under the professors' privilege (in Germany). In the latter case, we treat patents owned by BTG in the UK as firm owned patents.

In these p-score regressions, we find small deviations from the first column, but on the whole the results are similar. Interestingly, the number of words in the main claims of the patent becomes positively related to university ownership, as do the dummy for male inventors and the dummy for a postdoc degree (only in the second column).

Table 9a. Nearest Neighbour Matching results, complete sample

				Analytical se		Bootstrapped se	
	treated.	control	ATT	Std. Err.	*t*	Std. Err.	*t*
Patent Used	79	39	0.165	0.123	1.34	0.140	1.18
Commercial App	79	39	-0.025	0.126	-0.20	0.138	-0.18
Licensed	79	39	0.418	0.107	3.89***	0.096	4.36***
Start-up	79	39	0.114	0.095	1.20	0.086	1.32
Ln(Value)	79	39	-0.230	0.450	-0.51	0.430	-0.53
Fwd_cit	79	39	0.025	0.108	0.23	0.148	0.17

Table 9b. Nearest Neighbour Matching results, excluding defence patents

				Analytical se		Bootstrapped se	
	treated.	control	ATT	Std. Err.	*t*	Std. Err.	*t*
Patent Used	79	37	0.063	0.143	0.44	0.157	0.40
Commercial App	79	37	-0.139	0.146	-0.95	0.173	-0.80
Licensed	79	37	0.456	0.103	4.42***	0.107	4.26***
Start-up	79	37	0.076	0.113	0.67	0.170	0.45
Ln(Value)	79	37	0.086	0.501	0.17	0.644	0.13
Fwd_cit	79	37	-0.127	0.159	-0.79	0.248	-0.51

Table 9c. Nearest Neighbour Matching results, comparison only with firm-owned

				Analytical se		Bootstrapped se	
	treated.	control	ATT	Std. Err.	*t*	Std. Err.	*t*
Patent Used	79	32	0.203	0.149	1.36	0.177	1.14
Commercial App	79	32	-0.013	0.150	-0.08	0.181	-0.07
Licensed	79	32	0.405	0.129	3.14***	0.153	2.65***
Start-up	79	32	0.089	0.119	0.74	0.167	0.53
Ln(Value)	79	32	0.464	0.421	1.10	0.674	0.69
Fwd_cit	79	32	0.025	0.224	0.11	0.125	0.20

The average treatments effects as measured by setting up the control samples are documented in Tables 9a – 10c. Tables 9a-c documents results from a nearest neighbour matching method, while those in Table 10a-10c use kernel matching. The results in both tables have been generated by using the common support constraint.[18] Kernel matching (Tables 10a-10c) has the advantage that more observations are used, but standard errors for the observed treatment effect must be derived from bootstrapping. In terms if the qualitative conclusions, the results usually match between the two methods (we will discuss the one exception below).

In Tables 9a-10c, we observe only a significant, and positive, treatment effect for the licensing variable. The other variables are not significant, although the variable for overall commercialization (*Patent Used*) is positive. Interestingly, we observe the largest (but still insignificant) effect on overall commercialization when we compare university owned patents to firm owned patents only. The sign of the treatment effect for value and patent citations differs between the samples, but is never significant. These results are confirmed with kernel matching (Tables 10a-10c), with the exception of the overall commercialization variable in the complete sample (Table 10a). This is positive and weakly significant in Table 10a, while it was insignificant in Table 9a.

Thus, overall, we do not find strong evidence of an effect of university ownership on either commercialization or economic value of patents. Universities do tend to license more of their patents, but this does not lead very clearly to an increase in the overall rate of commercialization.

Table 10a. Kernel Matching results, complete sample

				Bootstrapped se	
	treated.	control	ATT	Std. Err.	*t*
Patent Used	79	239	0.186	0.107	1.74*
Commercial App	79	239	0.003	0.108	0.03
Licensed	79	239	0.439	0.076	5.78***
Start-up	79	239	0.101	0.080	1.26
Ln(Value)	79	239	-0.092	0.353	-0.26
Fwd_cit	79	239	-0.077	0.133	-0.58

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

Table 10b. Kernel Matching results, excluding defence patents

				Bootstrapped se	
	treated.	control	ATT	Std. Err.	*t*
Patent Used	79	240	0.052	0.116	0.45
Commercial App	79	240	-0.132	0.133	-0.99
Licensed	79	240	0.418	0.087	4.82***
Start-up	79	240	0.019	0.154	0.12
Ln(Value)	79	240	0.109	0.504	0.22
Fwd_cit	79	240	-0.187	0.151	-1.24

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

[18] 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.

Table 10c. Kernel Matching results, comparison only with firm-owned

	treated.	control	ATT	Bootstrapped se Std. Err.	*t*
Patent Used	79	160	0.190	0.156	1.22
Commercial App	79	160	-0.009	0.161	-0.05
Licensed	79	160	0.389	0.124	3.14***
Start-up	79	160	0.058	0.123	0.47
Ln(Value)	79	160	0.126	0.475	0.27
Fwd_cit	79	160	-0.008	0.144	-0.05

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

6. 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. About 80% of the EPO patents with at least one academic inventor are not owned by the university. 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-invented* patents. Once the data are corrected to take into account of the different ownership structure in Europe and the US, very simple back-of-the-envelop calculations suggest that the European academic system seems to perform much better than what was believed until now. In relative term, European universities patenting output lags behind only marginally to the one of US universities.

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.

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Appendix 1: Questions from the PatVal Questionnaire

F.2 Has the applicant/owner ever used this patent for commercial or industrial purposes?

F.3 Has this patent been licensed by (one of) the patent-holder(s) to an independent party?

F.4 Has this patent been exploited commercially by yourself or any of your co-inventors by starting a new company?

F.7 This is a hypothetical question: "Suppose that on the day in which this patent was granted, the applicant had all the information about the value of the patent that is available today. If a potential competitor of the applicant was interested in buying the patent, what would be the minimum price the applicant would demand?"

Appendix 2. Statistical methodology

A1 The control function approach[19]

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 $\beta_1 = \beta_0$ [20], this model can be further summarised:

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[19] See Wooldbridge (2002).

[20] 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 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:

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

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:

$$Y_i = \mu_0 + \tau D_{i,owned} + X_i \beta + \vartheta_i , \qquad (7)^{21}$$

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.

A2 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:

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

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:

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

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

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.

[21] 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).

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.[22]

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

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

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

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

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:

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

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:

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

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[23].

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