DIPARTIMENTO DI INFORMATICA
E SISTEMISTICA ANTONIO RUBERTI

SAPIENZA
UNIVERSITÀ DI ROMA

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Technical Report n. 2, 2012

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First version: October 11, 2012
This version: February, 16, 2012

Abstract

This paper presents the first assessment of the efficiency of the technology transfer operated by the French university system and its main determinants. The analysis is based on a detailed and original database of 51 TTOs, categorized by type of university they belong to, over the period 2003-2007. Overall, we find a low level of efficiency and both intra-category and inter-categories efficiency variation. The analysis of determinants showed that French TTOs efficiency depends extensively on the nature of the category (with universities specialised in science and engineering being the most efficient ones), on institutional and environmental characteristics. We found that both the seniority of TTO and size of the university have a positive effect. In terms of environmental variables, the intensity of R&D activity (both private and public) has a positive impact; however, in terms of growth rate, only the Private R&D activity seems to be the main driver. Lastly, we find that the presence of a university-related hospital is detrimental for the efficiency. An extended discussion of the results within the existing literature is also offered.

Keywords: Technology Transfer Offices (TTOs), French University System, Technical Efficiency, DEA, Bootstrap, Regional Growth

JEL Classification: C34; C44; D24

1. Introduction

The recent undergoing rapid changes in national systems of research and innovation, along with changes in economic conditions, are challenging European universities in acting a prominent, and more integrated, role within the national economy. This phenomenon is strictly linked to the increasing recognition of the importance of universities in producing, transferring and commercializing knowledge toward the knowledge-based economies. In this new context, universities are facing an important period of unprecedented change and transition, characterized by an increasing number of roles to play while endeavouring to have a more business-oriented behaviour focused on competition (Deiaco *et al*. 2009).

It follows a broader picture of complexity where several, and often divergent, interests of different stakeholders involved have to be addressed. In such a framework, successful technology transfer requires university administrators to think strategically about how that process might be the key of success. Strategic decisions, for instance, are related to the choice of resources allocation among possible modes of technology transfer, namely licensing, start-ups, sponsored research rather than other mechanisms of technology transfer that are focused more directly on stimulating economic and regional development (such as incubators and science parks, should be based on strategic choices).

In the last decade, policy makers of advanced industrial nations, Europe included, started to formalize the mechanism of university-industry technology transfer through the systematic development of Technology Transfer Offices (TTOs). As today, there is a lot of attention among policymakers and academics in understanding the TTO business profile, patterns of behaviours, and configuration of activities. This because the success of a TTO in technology transfer can result in pecuniary gains for the university and benefits for surrounding communities (Chapple et. al., 2005). The most crucial questions in mind of policymakers and academics are related to how productivity and efficient are universities in transferring technology and whether (or not) there exist key factors enabling the performance of TTOs.

There are several studies on the efficiency of TTOs, estimated from indicators of outputs and inputs of university technology transfer (for a recent review see Siegel, 2007). Most of the available empirical evidence is based on US data while evidence on European countries is much more limited, mostly due to the lack of data. Interestingly, a recent policy paper, summarizing some evidence on European universities, suggested that "perhaps the most important conclusion for policy making at this stage is to invest more in data and analysis" (Van der Ploeg and Veugelers, 2008). A common finding of this stream of literature is that accurate measurement of TTOs efficiency requires accounting for the influence of TTO specific characteristics as well as economic characteristics where the TTO is located. However, there remains little empirical evidence on European TTOs.

This paper attempts to fill this gap by studying university TTOs operating in France. Differently from the US and UK TTOs where the technology transfer process is more advanced, the French context offers an interesting laboratory to investigate TTOs operating at the first stage of their development, maybe closer to the Spanish context. In fact, while TTOs have been established very recently, it appears that the majority were established soon after the introduction of the first French government action taken in 1999. This action, the *July 1999 Innovation Law,* constitutes the main policy decision taken to favour technology transfer processes between universities and industry. Since its introduction, the number of TTOs increased but the need to accelerate and improve the quality of technology transfer process led to the introduction of other laws. For instance, a law for public accounting was adopted in 2001 to introduce a 'new public-management oriented' reform. This reform defines for all public interventions (including research and higher education) a set of objectives, along with corresponding sets of indicators patent-based to mirror technology transfer activities of French university. Given this context, it becomes important to assess the efficiency of French technology transfer activities at this stage to deeply understand how they are fulfilling their role in the early stage of development and possibly derive policy implications both for their future growth and also for new entering TTOs. If on the one hand, studying the technology process of French TTOs is interesting because allows to draw a picture on the functioning of a "young" system, on the other hand, it makes difficult to track the whole process (all possible technology transfer activities) for all the TTOs under investigation. We therefore model the process under an *operational* efficiency perspective, measuring how good are French TTOs in maximising the production of patent applications and other patent-related outputs, given the level of resources (inputs) used.

In this paper, we first compute the efficiency of individual TTOs and after that we examine the main determinants of individual TTO efficiency scores using the two-stage DEA approach proposed by Simar and Wilson (2007). According to this approach, individual TTO efficiency scores are regressed on some specific TTO characteristics as well as the regional economic conditions and R&D activity.

Summing up, this paper extends the current performance TTO literature along several dimensions: (i) it analyzes TTOs in their early stage of development, (ii) it provides the first quantitative assessment of French TTOs efficiency based on an original and detailed dataset, enriching the European empirical evidence on technology transfer, (iii) it applies a recently developed statistical approach based on Data Envelopment Analysis and bootstrapping techniques (Simar and Wilson, 2007); (iv) lastly, it discusses policy implications of the results compared with existing studies on other countries.

The remainder of the paper is organized as follows. Section 2 presents a literature overview on TTOs efficiency; Section 3 examines the French context and our modeling of the activities of French TTOs; Section 4 describes the methodology applied; Section 5 illustrates the data and formulates the production models. Section 6 is devoted to the investigations on the TTOs (in-)efficiency determinants. Section 7 reports the empirical findings. In the framework of the recent institutional policies, the final section discusses the main results comparing them with the existing literature and outlines further developments

2. A selected review of the literature

Since the pioneering contributions of Thursby and Thursby (2002) and Thursby and Kemp (2002), the assessment (and explanation) of TTOs performance has remained the main issue of debate among academics and policymakers. If on the one hand it is increasingly attracting the attention of policymakers, as documented by the large amount of policy initiatives in this field (e.g., European Commission 2004, 2008), on the other hand this issue is not well documented in the literature, in particular for the European case.

Our analysis on French TTOs is in the same spirit as those empirical studies of the performance of TTOs with respect to licensing and patenting activities (for a more general overview, see Siegel, 2007). Overall, we selected a total of six papers, of which four deal with the US (i.e. Thursby and Thursby, 2002; Thursby and Kemp, 2002; Siegel et al., 2003; Anderson *et al.*, 2007), one with the UK (Chapple et al., 2005), one with Spain (Caldera and Debande, 2010) and one based on a cross-country comparison US vs. UK TTOs (Siegel *et al.*, 2008). This strand of literature focuses on the performance measurement with two crucial policy-related questions in mind: the first is "Should TTOs improve their ability to operate by adjusting their production mix?", the second "Which are the key factors enabling TTOs to operate more efficiently? Are they related to either specific TTO characteristics and/or to certain types of TTOs? And/or to the intensity of direct and indirect connections the TTO might establish with region where they are located?". Empirical evidence supports the second argument showing that factors, unrelated to the production plan, do matter for the effectiveness of TTOs. However, the direction of the influence of these factors (positive or negative) remains unclear, due in part to the use of different approaches (parametric vs. non-parametric approach) and/or to different TTOs activities analyzed (single output vs. multi-output). It should be noted that very often researchers are limited to analyze partial TTO production process as TTOs are far from covering all the activities (early stage of development) or data availability is fragmented (e.g., Bonaccorsi and Daraio, 2007) or data may be heterogeneous (see Daraio *et al.*, 2011). Overall, these issues rule out the possibility to achieve a general consensus.

Looking at the construction of output distance function, several approaches have been used. For instance, the works by Thursby and Kemp (2002) and Anderson *et al.* (2007) is based on DEA approach, allowing for the multi-outputs structure. Outputs are measured both in terms of physical and monetary values such as the number of licences executed, the number of invention disclosures, the number of patent applications and the amount of industry sponsored research and royalties received. On the contrary, Siegel *et al.* (2003) and Chapple *et al.* (2005) employ the stochastic frontier estimation approach restricting the production process to one single-output structure. They obviate the failure to capture the dual strategy of license numbers and license income maximization by estimating two frontiers, using one output at a time. Siegel *et al.* (2008) extend the previous works by constructing a multiple-output distance function from a parametric approach, including number of licenses, licensing income, as well as the new university startups generated and equity banked new university startups. By using a simple linear regression analysis, rather than frontier approach, Caldera and Debande (2010) estimate several specification models where the output of TTOs are measures in terms of income (from R&D contracts, licensing), number of R&D contracts, licensing agreements and the number of spin-offs. Overall, these papers investigate the TTOs efficiency accounting for both physical and monetary outputs. While efficiency related to the former is closer to the concept of technical-efficiency, the second is closer to profit-efficiency. It should be borne in mind that, depending on the approach taken, the determination of factors affecting the efficiency might change, as is also shown in the empirical evidence.

The two sets of variables under investigation are: (i) specific TTO features and specific group features, (ii) regional macroeconomic features. Regarding the specific TTOs characteristics, several dimensions have been tested. First, the presence of a medical school. It is generally assumed that universities with medical schools are likely to be more efficient than those without because it is easier for them to conduct clinical trials and produce a large fraction of university licenses related to biomedical inventions. However, empirical evidence is controversial. Some papers show that the presence of medical school dampens the efficiency of US (e.g., Thursby and Kemp, 2002; Anderson *et al.*, 2007) as well as of UK TTOs when their strategy is license income maximization (Chapple *et al.*, 2005). This efficiency reduction may be related to the heavy services commitments of medical school or to differences in the health product market. On the other hand, other studies do not show any statistically significant impact on the efficiency, such as is the case of Spanish TTOs and US TTOs under both output assumptions (Siegel *et al.*, 2003). However, the analysis proposed by Siegel *et al.* (2008) shows that universities with medical schools are more efficient. These controversial differences in results might be due to different production process characterization.

Second, the experience of TTOs in channelling technology. It is assumed to be directly proportional to the age of the TTO and pivotal to possibly benefit from "learning by doing" effects. However, this factor plays a dual role, depending on the strategies pursued by the TTO's management, as also pointed out by empirical results. For the US TTOs, Siegel *et al.* (2003) show that older TTOs are more efficient when the income maximization strategy is employed. However, Siegel *et al.* (2008) find opposite results. These controversial results might be explained by the differences in the number of outputs used in the estimation. By constructing a frontier based on a larger set of outputs, the latter paper unveils that older TTOs are more likely to be interested in alternative strategies of technology transfer. Any statistically significant influence of age on US TTOs is found under the number of licences maximization. The analysis of UK TTOs shows, on the other hand, that age has a negative effect on efficiency but only when the objective is the maximization of the number of licenses, possibly reflecting diseconomies of scales or efforts to employ strategies different from licensing. For the case of Spanish TTOs no statistically significant impact is found (Caldera and Debande, 2010).

Third, the TTO ownership. Some papers distinguish between private vs public universities as public universities might be less flexible in technology transfer process in the interaction with firms and also less focused on the technology research at high income potential (Siegel *et al.*, 2003). Caldera and Debande (2010) support this hypothesis as they find public ownership to have a negative effect on licensing for the Spanish case due to the fact that public universities in Spain do not have close links to the private sector.

The second group of variables under scrutiny is a set of regional macroeconomic characteristics and regional R&D intensity. It is generally assumed that the integration of a TTO with the local area enhances efficiency. For this set, empirical evidence provides a more general consensus. In particular, TTOs in regions with higher R&D activity are found to be more efficient in generating new licences and/or other forms of outputs, with the exception of income, for the case of the UK and the US. TTOs (Chapple *et al.,* 2005; Siegel *et al.,* 2003; Siegel *et al.,* 2008). Moreover, the regional development measured by the regional GDP per capita or annual real output growth is found to have a positive effect on the UK TTOs in generating licence income and for both the UK and the US (Siegel *et al.,* 2003, Siegel *et al.,* 2008) in also generating new licences jointly with other strategies.

The Table 1 below summarizes the main results of the selected studies from the literature that were relevant for our empirical analysis. We will consider the existing empirical evidence in the Empirical Results Section where we will discuss the main findings of our analysis.

[TABLE 1 AROUND HERE]

Our paper contributes to the literature summarized in the previous table in three directions.

First, to the best of our knowledge, this is the first study that examines the French university system. Secondly, we use a recently developed methodology to investigate the determinants of the heterogeneity in performance across TTOs. Thirdly, we discuss our results in relation with existing studies on other countries and discuss the policy implications.

3. Modeling the activity of French TTOs

3.1 The French public research and higher education system: State and evolution

Over the last two decades, the French research and higher education system has undergone structural changes which led to the progressive disappearance of the dominant role of the Colbertian State (Mustar and Larédo, 2002). In fact, the French system was based on a very specific interventionist model, characterized by four main features, which emphasised the dominant weight of large civil and defence programmes, the division between universities and the French national research council (CNRS), the congenital separation between research and firms and finally the concentration of public support on a few large companies. This model has been undergoing fundamental changes since the 80s, giving way to a more complex system, where a relative reduction of the resources devoted to public research, the increase of the institutional complexity and the need to serve a "third mission" of contributing to local economic development (Etzkowitz, 2002) are the main challenges that need urgently to be faced.

The French research and higher education system is largely public. It includes all universities, most of the Higher Education Institutions -HEIs - (except some business schools), and the large research organizations (PROs). Moreover, a high share of research-related resources of HEIs and PROs also comes from public sources compared to other possible sources (contracts with firms or not-for-profit organisations, donations, Intellectual Property Rights -IPR- incomes, etc), most teachers-researchers and a very high share of researchers in universities and PROs are civil servants.

The French research and higher education system is composed by: 88 universities active in higher education teaching and, at different level, in research activities; several dozens of HEIs, including most "Grandes Ecoles" in engineering and public administration; and around 25 PROs, some mainly oriented towards fundamental research, (such as CNRS, INSERM, INRA and so on), others mainly oriented towards applied research and commercialization (such as CEA, CNES, ADEME and so on)[1]. We will concentrate our analysis on the main universities under the supervision of the Ministry of Education, Higher Education and Research (MENESR)[2], excluding the PROs. The selected group shows high level of hetereogeneity, also given by size and discipline coverage[3].

A key aspect of the research and higher education system is its "duality", in which large PROs stand beside universities[4]. Although the separation tends to be increasingly blurred, this breakdown still has a very strong influence on research activities, governance, allocation of resources, and so on. Indeed, 44% of the approximatively 3,000 university research units (including all the top ones) are "joint research units" between PROs organized at national level (especially CNRS and INSERM) and individual universities organized at local level (those "joint research units" sometimes involve more than one university and more than one PRO). A joint research unit, according to local agreements, can follow the procedures and the organisational setting of one of the institutions[5] supervising the research unit. Of course, this "duality" induces some constraints and structural bias on the data collection and on the database used in the analysis[6]. This specificity of the French HEI system may have an influence on the technology transfer activities and therefore should be taken into account.

The French government developed an explicit policy to deal with the supposed weakness and difficulties of the research system. It did implement new policy tools and reforms, most of them aiming to promote public research-industry interactions. The July 1999 *Innovation Law* was the main decision taken to promote the creation of innovative technology companies and the

[1] But the creation in 2005/06 of two agencies (ANR – National Agency for Research, and AII – Agency for Industrial Innovation, more on the industrial research side) may tend to re-centralize a large share of the funding role of more classic agencies, at least with regard to project-based funding.
[2] In addition, on the upstream end of the research spectrum there are very few big foundations, which mainly are in medicine (such as Institut Curie and Institut Pasteur). At the downstream end of the research spectrum a large number of Technical Centres (sector oriented) and Technologies Resources Centres (often regionally based) co-exist.
[3] We will control for them in our second stage analysis.
[4] Another duality resides on the HE side, where universities stand beside the so-called Grandes Ecoles.
[5] Even if various common rules and procedures, forms of coordination and mutualization processes have recently been fostered.
[6] For a deeper discussion on this issue, see Bach and Llerena (2007).

technology transfer of public research towards industry. The Innovation Law imposes to all universities to develop an explicit policy for 'commercialising' their results. Later, the frame was adjusted to allow for the creation of 'Services d'Activités Industrielles et Commerciales: SAIC' ("Department for industrial and commercial activities"), in other words of Technology Transfer Offices (TTOs). In this context, some of the private accounting rules were introduced for technology transfer activities, although TTOs are not independent legal entities.

For the academic researcher, the Innovation Law implements an incentive system to become more entrepreneurial and, *vice versa*, for the existing firms to increase their scientific expertise. In particular, it was intended to encourage: (i) the creation of new firms; (ii) an increase in the number of technological innovation and research networks; (iii) financial and legal reforms to benefit innovative companies. The main purpose of our paper is to assess the relative efficiency of the TTOs, many of them established after 1999.

In addition, and in parallel, in 2001 a law for Public Accounting (Loi Organique sur la Loi de Finance, LOLF hereafter) was adopted. This new reform, called *New Public Management oriented Reform,* affects all state expenditure, in a framework of re-organization of public intervention into broad missions, broken down into programs, and finally into actions. A set of objectives, with corresponding sets of indicators are assigned to all public expenditure. University and PRO activities are aligned with the mission "Research and Higher Education". To monitor science-industry relations, the indicators used for university research activities that refer to technology transfer activities are mainly based on patents (Assemblée Nationale, 2005).

Therefore, the pressure for developing technology transfer indicators and corresponding statistics came directly from govermental authorities in order to monitor the efficiency of public spending, in particular in the science and techonology field. As a matter of fact, at least during the period under consideration in our paper (2003-2007) the main indicators of technology transfer were based on patent applications in a broad sense, including extensions, and similar IPR instruments for software. For this reason, in the empirical setting of our analysis we use as proxy of the outputs the patent related measures. Of course, we are aware that our choice has its own limitations, as pointed out by Bach and Llerena (2007, p. 5): *"especially since institutionalization of Technology Transfer (TT) is quite recent in most of the French universities, TTOs are far from covering all TT-related activities. It is even doubtful whether there is in each HEI or PRO a systematic and coherent information system allowing the recording of TT activities in a comprehensive way. This makes it difficult to get a precise estimate of the relative importance of the "hidden" TT activities, especially of course those conducted on a purely individual (and frequently "off-duty") basis by researchers."* Nevertheless, our paper provides the first assessment of the (in-)efficiency levels of the TTOs in France, following the explicit policy to develop patent related indicators in the early 2000s. Moreover it investigates the determinants of inefficiency differentials and contributes to filling the gap existing in the literature, related to the lack of empirical evidence on the French system of university TTOs.

3.2 Defining TTOs' activities to assess their efficiency

The Technology Transfer Office (TTO) has a specific organizational arrangement designed to encourage the University-Industry Technology Transfer (UITT) process and commercialization. Our purpose in this paper is to analyze the relative efficiency of French TTOs, especially after the reforms described in the previous section, without devising our own output measures but using metrics proposed by the law.

TTOs are considered as structures having their own production process, transforming the general knowledge produced by researchers (and research units of a given research institution such as universities) into transferable knowledge, to be used by firms. According to the French legislator, the main products of the process are patent related outputs, including in particular patent applications. Indeed, as also Thursby and Thursby (2002) pointed out, in the evaluation of TTOs processes one should take care of the bias due to the delays between the inputs used to produce issued patents and avoid it by using patent applications. Therefore we use patent applications and their extensions as our proxy for French TTOs. As already explained in the previous section, these metrics were used by the Ministry in charge of research to monitor the TTOs' activity during our period of observation.

In our model, the TT process of a TTO (see Figure 1) uses mainly two types of inputs: the first one is related to the means at the disposal of TTOs to operate and transform general knowledge into codified knowledge, i.e. into patent applications. It is mainly composed of their own personnel and some external advice (mostly legal). But the main input is the knowledge produced by the university, most of the time integrating novelties which are considered as some kind of "raw" materials, usually at an early stage of development. We propose to use scientific publications as a proxy for this input.

Of course, as any production process, the outcomes are context dependent; we will consider explicitly two types of context: the external one – i.e. the regional economic characteristics and the internal one – i.e. the university characteristics, because each university has its own specificities, mainly related to the disciplines covered, influencing the production opportunities (possibilities) of its TTO.

[FIGURE 1 AROUND HERE]

4. The methodology: A two stage semi-parametric bootstrap based approach

We examine the determinants of (in-) efficiency by using a two-stage DEA estimation based on the bootstrap procedure proposed by Simar and Wilson (2007), wherein technical (in-)efficiency is estimated in the first stage and then regressed on a set of external (environmental) factors in the second stage. Beside the major advantages related to DEA estimation, that is the lack of any assumption on the functional form of the production frontier and the simultaneous use of multiple inputs and outputs, the bootstrap procedure overcomes some of the main issues related to the traditional two-stage DEA analysis (also acknowledged by Chapple *et al.*, 2005) by allowing for (i) the bias correction incorporated in DEA due to the uncertainty associated to sampling variation, particularly evident in the case of small sample sizes, as in our analysis (ii) accounting for the serial correlation structure of DEA efficiency scores when the regression of these scores is estimated on the environmental variables at the second stage.

We assume that TTOs share the same production frontier, which respects standard regularity conditions. Let each TTO activity be described by a set of inputs (resources) $x_k \in \Re_+^H$ which are converted into a set of outputs $y_k \in \Re_+^M$ via an underlying production technology. It can be characterized by the technology set, defined as:

$$\Psi = \{(x, y) \in \Re_+^H \times \Re_+^M \mid x \; can \; produce \; y \} \tag{1}$$

Since the real technology is unknown, its estimation is required. Thus, at the first stage, we first estimate (1) via DEA, as follows:

$$\hat{\Psi}_{DEA} = \Big\{(x, y) \in \Re_+^H \times \Re_+^M \mid \sum_{k}^{N} z_k y_k^m \geq y^m, m = 1, \dots, M$$

$$\sum_{k=1}^{N} z_k x_k^h \leq x^h \;\; h = 1, \dots, H \;\; for \; (z_1, \dots, z_N), \; such \; that \sum_{k=1}^{N} z_k = 1; \;\; z_k \geq 0 \quad k = 1, \dots, N \Big\} \tag{2}$$

where $z_k \geq 0$ are the intensity variables over which the maximization is made. The estimation of the technology frontier makes efficiency measurements possible. Various measures of efficiency are possible. We use the Debreu (1951)-Farrell (1957) measure of (in-)efficiency as radial distances to the estimated frontier. In the paper we adopt an output oriented framework: given the level of resources (inputs) used by university TTOs, they look at the maximization of their outputs. Then the Farrell output oriented measure of technical (in-)efficiency score is given by:

$$\hat{\lambda}(x, y) = \max\{\lambda \mid (x, \lambda y) \in \hat{\Psi}_{DEA}\} \tag{3}$$

In this approach, a TTO is considered efficient if it lies on the "efficient" estimated frontier, i.e. if $\hat{\lambda}(x_k, y_k) = 1$, otherwise it is inefficient and $\hat{\lambda}(x_k, y_k) \succ 1$. $\hat{\lambda}(x_k, y_k)$ measures the proportional increase of outputs that a TTO could realize using the same level of inputs it is actually using. The main limitations of DEA are its deterministic nature (all the distances from the efficient frontier are assumed to be inefficiency) and its biased estimation. Hence we control for the uncertainty of DEA scores estimating their bias and confidence intervals by using a consistent bootstrap approximation of the efficiency distribution (see for more details Simar and Wilson, 2000).

At the second stage, we analyze the dependency of the efficiency specific to each TTO on a set of environmental factors, Z_k. We follow Simar and Wilson (2007) by applying: (i) a truncated regression to consistently estimate the parameters by using maximum likelihood and (ii) a consistent bootstrap for inference in the case of truncated regression. The bias corrected efficiency scores, resulting from the first stage, enter the regression as dependent variable in the second stage. As efficiency scores are bounded at unity, the distribution of the error term is restricted. Formally, the model is defined as follows:

$$\hat{\lambda}_k^c \approx Z_k \beta + \varepsilon_k \quad \forall k = 1, \ldots, N \tag{4}$$

where $\varepsilon_k \sim N(0, \sigma_\varepsilon^2)$ such that $\varepsilon_k \geq 1 - Z_k \beta, \quad \forall k = 1, \ldots, N$, being the dependent variables bounded by unity. The estimation procedure and the bootstrap algorithms are described in more details in Simar and Wilson (2007).

5. Data and production models

5.1 Selected Inputs and Outputs

Data from French TTOs were collected by BETA (Bureau d'Economie Théorique et Appliquée, UMR UdS-CNRS 7522, Strasbourg) in 2005, 2007 and 2009[7], during regular surveys, funded by the French Ministry in charge of Higher Education and Research. The surveys had the support of the national French TTO network (CURIE), CPU (the Conference of University Rectors) and CDEFI (Association of Engineering Schools Directors). The purpose of the surveys was to build a first comprehensive database, focused on variables characterising different dimensions of

[7] See Bach and Llerena (2006, 2008, 2010).

technology transfer by Higher Education Institutions such as Universities and Engineering Schools (generically called "universities" thereafter). A first questionnaire was elaborated in 2004 and e-mailed to 74 universities. In 2007, a more detailed version was submitted to a larger number of universities (96 universities). More recently, the survey was launched on line, allowing for further refinements of the questions and a more efficient process of data collection.

The description of the UITT process, reported in Section 3.2 helped us identify the appropriate set of inputs and outputs to be included in the production function. For French TTOs the most critical outputs (we call "core outputs") are patent applications (PAT_APP) and software applications (SW_APP). However, French TTOs are also active in releasing patents extensions. Therefore, we include both number of patents with submitted extension requests (PAT_EXT) and number of extensions required (Nb_PAT_EXT) as additional outputs and call them "patent-related outputs". As input measures, we choose labour, measured by the number of full time equivalent employees in the TTO (ETP) and the number of publications (expressed in fractional terms) (PUB)[8]. The number of publications is used as a proxy of the stock of knowledge available to the TTO.

In France, the UITT process is still very slow and time lags might occur between the inputs used and the outputs produced, causing a mismatch in the production process. For instance, inputs used today will produce outputs in the coming years. In order to prevent any error from time lags, we base our analysis on 5-year (from 2003 to 2007) averages of the data, as in previous studies (e.g., Thursby and Kemp, 2002; Anderson *et al*., 2007). Although several universities reported numerous zeros, we end up with a database comprehensive enough to carry out an efficiency assessment: 51 TTOs, covering all the categories of disciplinary fields of the related university: (i) Polyvalent University with Medical School (UPAM), (ii) Polyvalent University without Medical School (UPSM), (iii) Polytechnics (INP), (iv) Science Universities (USC), (v) Social Science and Humanities Universities, Law and Economics (USH/D-E), (vi) Engineering School (ING).

[8] Elaborated by OST using Web of Science.

Table 2 presents the summary statistics of input and output variables for the pooled sample according to the categories of disciplinary field of the related university. The statistics suggest heterogeneity across groups in terms of their input and output compositions, justifying our discussion of the results according to this breakdown. Heterogeneity is also found within each group, as the high value of standard deviation shows. This reflects the fact that TTOs have some specific characteristics, unrelated to the group of belonging.

Not surprisingly, USC universities employ, on average, the largest amount of ETP and have the largest amount of technology stock. They seem to be very far from using similar amount of inputs used by other universities. ING and UPAM universities are more similar, in particular in the availability of amount of technology stock, while UPSM and USHS/D-E have a TTO staff similar, on average, to the staff of UPSM, though they differ in the amount of technology stock.

USC universities have, on average, the largest patent application activity as well as the largest amount in the remaining activities. ING and UPAM, on average, seem to have similar patent application production but different productions in the remaining activities. Although USHS\D-E, in principle, might be less involved in technology transfer, they exhibit modest outputs in all the activities and outperform UPSM in software applications. If we look at the variability in output production within each group, evidence of it is found, in particular across USC TTOs.

These considerations lead us to expect evidence of quite substantial inefficiency, which might stem simply from other factors (such as university category, intrinsic characteristics of TTOs, and regional influences) rather than those related to competencies in technology transferring. We, therefore, support the hypothesis that there may be different ways to approach the technical efficient frontier.

[TABLE 2AROUND HERE]

Lastly, from Table 2, it should be possible to deduce the importance of accounting for both the core (patent and software applications) and the patent-related outputs (extended output portfolio with the number of patents whose extension is submitted and the number of extensions), as the volume of the latter could not be disregarded.

[TABLE 3 AROUND HERE]

However, by inspecting Table 3, we find high levels of correlation (higher than 87%) between PAT_APP and both PAT_EXT and Nb_PAT_EXT. We therefore model the production process according to two inputs-outputs configurations: one wherein we select as outputs patent and software applications (Model 1) and another one wherein patents whose extension is submitted and extensions of patents are also included. Model 2 aims to capture the entire dimension of technology transfer whereas Model 1 captures only the core activities. The interpretation from a statistical point of view, however, is that the two models are likely to produce similar estimates due to the correlation among variables. However Model 2 is more likely to suffer from the curse of dimensionality, being estimated on a higher dimensional space (more inputs and outputs), implying a lost in the level of statistical precision as well as lower discriminatory power among DEA estimates. Therefore, to better disentangle the simultaneous effects of different exogenous variables on DEA estimates, we restrict the second stage to the analysis of Model 1.

5.2 Factors affecting the TTOs' (in-)efficiency

In this section we describe candidate determinants of (in-)efficiency. The first set is related to possible source of heterogeneity of TTOs (Bonaccorsi and Daraio, 2007; Daraio *et al.,* 2011) related to university specificities, including disciplinary mix. The second set is related to the macro-economic level of regions where TTOs are located as well as the interaction between TTOs and R&D activity of the region where the TTOs are located. Also in this case, we assume that they play an important role in the French context due to possible agglomeration effects and economic disparities across French regions. We analyse them in turn.

Specific and group-specific TTO characteristics

Four dimensions of heterogeneity are controlled for, namely TTO age, university size, presence of a university-related hospital, and disciplinary field. Contrary to other studies, we do not control for the ownership (private vs. public) as French TTOs are related to public universities.

Age (AGE). We use this variable, measured as the length of time that has passed since the creation of technology transfer, to account for possible "learning by doing" effects in the production of technology. It might occur that some older TTOs benefit from their experience compared to the younger TTOs. We expect a positive impact on TTOs efficiency. In fact, since their creation, TTOs focus their strategies of technology transfer in engaging the "best" inventions to be transformed into patents, and source of income afterwards.

Number of Professors (SIZE). This is used to proxy the size of the university related to the TTO as larger universities are expected to produce more research, and therefore, to be more prone to disclose their inventions. For instance, Caldera and Debande (2010) find that the number of professors working at the university has a significant positive impact on TTO efficiency (when the output is measured in terms of R&D contract income and number of contracts).

University-related hospital (HOSPITAL). In France, there are USC universities with both medical schools and university-related hospital while UPAM universities may have only the medical school. It is therefore more informative for the French case to control for the presence of a university-related hospital (dummy variable equal to 1 if there is a university-related hospital, 0 otherwise). The presence of a university-related hospital guarantees significant ongoing medical research, whereas a simple medical school reveals only a training activity. It is usually thought that medical research is an important source of technology transfer. However, it might happen that both institutions, the university and the university-related hospital, that are legally independent entities, try and capture the potential technology transfer coming from life and medical sciences. For this reason the impact of the presence of university-related hospital is uncertain and it depends on the competition between the two institutions (namely the university and the university-related hospital).

In the literature in fact results are controversial and also for the French case the impact of this variable is uncertain.

University disciplinary category dummy variable. Lastly, we control for group-specific features associated to each university disciplinary category (ING, UPAM, UPSM, USC, and USHS). We use a total of 5 dummy variables to capture any possible effects. This helps us investigate whether the inefficiency of some TTOs associated to less innovation-oriented disciplinary fields (such as USHS) is driven by an inefficient production plan of the TTOs or whether it is driven merely by intrinsic aspects of the group. In line with the literature, we expect that the scope of disciplines does matter.

[TABLE 4 AROUND HERE]

Table 4 shows a descriptive analysis of the variables AGE, SIZE and HOSPITAL.

By inspecting Table 4, it appears that science universities (USC) are the most experienced (mean: 15,215 years). The average is well beyond the time passed since 1999 when the ‘Innovation law’ was established to make the existence of an explicit technology transfer policy at the university level compulsory. It is also the case for the category ING (engineering schools) and UPAM (i.e. universities with medical schools). Concerning the size of university, we can see that there exists higher level of homogeneity across TTOs. The presence of the hospital, on the contrary, is a specific characteristic associated to UPAM and USC universities.

Regional macro-economic characteristics and regional R&D intensity

Although we are studying TTOs operating in the same nation, regional economic development is likely to differ substantially. France is not an exception as it is characterized by high differentials in territorial dynamics and regional policies for research and innovation (OST, 2010). Overall these differences might differently affect the way TTOs operate.

We control for that by using a set of variables, including both the economic macro-economic characteristics and the R&D intensity of the region where the TTO is located. In the line with the approaches used in the literature, we use GDP per capita as index of regional development. However, contrary to other studies, we split regional intensity in R&D into public and private R&D intensity in order to distinguish between inside pushing dynamics (public expenditure) and outside pulling one (private R&D). In particular, we measure the public (and private) R&D intensity as the public (and private) R&D expenditure per capita. We expect outside pulling as a driver of efficiency.

Since we analyze the average-efficiency of TTOs over the period 2003-2007, we also control for possible effects due to the rate of growth both of the GDP per capita and the R&D intensity, expressed as changes over the entire period. Specifically, they are: Growth Regional GDP intensity which is the growth rate of GDP per capita; Growth Public R&D intensity which is the growth rate of public investment in R&D; Growth Private R&D intensity is, finally, the growth rate of private investment in R&D.

6. Empirical Results

[TABLE 7 AROUND HERE]

We first present the estimates (biased and bias-corrected respectively) and confidence intervals for the DEA Model 1 and Model 2. The results from the first stage provide insights into whether (or not) disciplinary areas and intrinsic characteristics are valid candidates to explain efficiency differences among French TTOs. Results from the second-stage regression provide estimates of the effects of individual specific, group-specific and macroeconomic characteristics.

As the aim of the analysis is to explain the inefficiency, efficiency scores are reported à la Farrell (1957): the closer the score to unity, the more efficient the TTOs. However, in the discussion we also report between brackets the efficiency score à la Shepard (1970), which are the reciprocal of the Farrell efficiency scores and represent the relative %-level of efficiency, to easily compare our results to previous studies. Preliminary tests on the type of returns to scale exhibited globally by the technology have been carried out.

Preliminary consideration: testing the returns to scale of the frontier

Before starting the DEA frontier estimation, one might wonder which returns to scale are exhibited by the technological frontier: either constant (CRS) or variable (VRS). Previous studies on the performance of TTOs (e.g., Siegel *et al.*, 2003 Chapple *et al.*, 2005, Siegel *et al.*, 2008) investigated the presence of returns to scale at local level with the aim of finding whether an increase or reduction of the scale could improve the efficiency of the unit. They showed that TTOs are more likely to work at constant or decreasing returns to scale. However, this approach *per se* does not define the type of returns to scale of the frontier (technology). Thus, departing from the past analysis, we investigate the type of returns to scale which characterizes the whole technology, shared by French TTOs and defined by the best performers. We formally test whether the frontier globally exerts constant (CRS), non increase (NIRS) or variable (VRS) returns to scale in a Monte Carlo scenario (for more details see Simar and Wilson, 2002). The test results lead us to reject the null hypothesis of global CRS at 5% level for both models (p-values equal to 0.0440 for Model 1 and p-value equal to 0.0405 for Model 2), accepting global VRS for French TTOs. This implies that our estimation accounts for size-effects related to TTOs.

First stage regression results: Group-efficiency and specific TTO efficiency results

We report the geometric average of the (bias-corrected) efficiency by categories of TTOs and of the whole sample, along with the individual TTO efficiency scores (see Tables 5 and 6). The first and the second columns report, respectively, the biased efficiency (Eff.) and the bias-corrected efficiency (BC-Eff.). The third and fourth columns report the bias term (Est. Bias) and the estimated standard deviation (Est-Std.). The final two columns provide the lower bound (LB) and upper bound (UB) of the 95% confidence interval of the bias-corrected efficiency scores. The estimated bias is negative for all the TTOs efficiency scores, suggesting that our original efficiency is overestimated, and the standard deviation indicates that the estimated bias is statistically different from zero in nearly all cases. Given that, we discuss the results in terms of bias-corrected efficiency and the relative confidence intervals to control for uncertainty.

[TABLE 5 AROUND HERE]

[TABLE 6AROUND HERE]

A key factor shown in Tables 5 and 6 is that in both models there is substantial inefficiency present in our sample. Considering the model based on core outputs (Model 1), the interpretation is that the average Farrell TTOs operate at 2.202 (49.5%) efficiency. In other terms, given the inputs, French TTOs could increase their outputs of the double. Considering the model based on both core and related outputs simultaneously (Model 2), similar results are found but, in this case, the French TTOs operate at slightly higher efficiency, which is 1.961 (or 51%). This might be attributed to the fact that Model 2 captures all TTOs activities, accounting therefore for different strategies pursued. Compared to findings in previous papers, our results are partially consistent. In fact, they are in line with UK findings (Chapple *et al.,* 2005), which were based on a single output (either number of licenses or licensing income). However, they differ from results based on joint analysis of US and UK TTOs (Siegel *et al.*, 2008), where the average efficiency is set at 70.7% and the results on US TTOs (Thursby and Kemp, 2002), based on a multi-output model, where the average efficiency is set at 82%. Of course, the comparison with previous studies has to be taken with care because different methods are applied to estimate the efficiency.

However, taken together, our results clearly highlight that the French system suffers from inefficiency. This finding leads us to suspect that the entire inefficiency might not be entirely attributed to the inability of French TTOs in the technology transfer function (as also found for US and Spain TTOs in previous papers), but rather be due to some intrinsic features of TTOs (heterogeneity between groups of TTOs and within TTOs groups) as shown in Section 5, possible statistical noise, etc. Therefore, the low level of the overall performance should not be interpreted as a standing alone result but requires more careful investigation and a joint interpretation with more detailed efficiency estimations. To this purpose, we look at first at point group- and individual-estimates, and then turn to confidence intervals.

In general, we find that there are two groups performing better than others and at a higher degree of efficiency than the overall sector. Comparing the categories of TTOs, in Model 1, the results show that science university (USC) TTOs are the most efficient group, followed by Engineering School (ING) TTOs and Polyvalent university with medical school (UPAM) TTOs. On the contrary, the typical Polyvalent university without medical school (UPSM) TTO and the Social and Human Science University, Law and Economics (USHS/D-E) TTO rank at the bottom. We conjecture that these results could reflect the fact that USC and ING TTOs have structures, processes and strategies focused on processing more applied knowledge rather than a purely theoretical knowledge, and with better market opportunities, as opposed to TTOs affiliated to UPSM and USHS/DE. Under Model 2, the ranking is slightly different: Engineering School (ING) TTOs are the most efficient, followed by the science university (USC) TTOs and the Polyvalent university with medical school (UPAM) TTO. Also, at the bottom of the ranking, we see that, unlike in Model 1, Social and Human Science University, Law and Economics (USHS/D-E) TTOs perform better than Polyvalent university without medical school (UPSM) TTOs.

Further, the standard deviation of the group efficiency seems not to be negligible, as is also confirmed by the boxplots depicted in Figure 2. We therefore turn to investigate intra-group efficiency to possibly find internal variations. In Model 1, UPAM TTOs efficiency scores vary from 1.249 to 4.677 while USC TTOs efficiency scores vary from 1.271 to 4.645 if bias-corrected. Higher levels of variability are found for the remaining groups, ING, USHS/D-E and UPSM in order. In Model 2, the variation is still present and has similar degree as in Model 1 for most of the categories, expect for UPAM and USHS/D-E which seem to perform better. In addition, the efficiency heterogeneity structure associated to each group is similar across groups, as shown by the similar efficiency score of TTOs belonging to different groups, except for USHS/D-E. Taken together, these findings suggest the lack of clear evidence to what extent the disciplinary field specialization (e.g. basic research vs. teaching) influences the TTOs performance as also other factors, more related to the specific TTO, might play a crucial role.

[FIGURE 2 AROUND HERE]

Consequently, empirical evidence requires careful interpretation when conclusions are drawn relying upon aggregated efficiency point estimates both at category and system levels. In this respect, the analysis of confidence intervals might help us draw additional information on the precision of our estimates as they indicate how sensitive a particular TTO's efficiency score is to variations in the efficiency of other TTOs in the sample. Moreover, confidence intervals allow us tp easily ascertain not only the precision of each TTO performance but also whether there is any empirical evidence to conclude in favour of the null hypothesis that establishes that two TTOs are equally efficient (overlapping of the confidence intervals).

In our case, several confidence intervals overlaps within each group exclude the presence of high degrees of heterogeneity at group level but rather they suggest the presence of possibly 2 or 3 TTOs sub-categories equally efficient, yet clear intra-group dissimilarities are still present.

Thus, summing up, the joint analysis of point and confidence intervals highlights that (i) there is a kind of heterogeneity in the performance of French TTOs, (ii) both specific group and individual TTO seem to drive the inefficiency, the latter having the highest impact.

Second stage: assessing the impact of factors affecting TTO efficiency

In the second stage of the analysis, we investigate possible determinants of efficiency by estimating the econometric model described in equation (4) reported above using the individual TTO bias corrected inefficiency score as the dependent variable, and the set of regional macroeconomic indicators, regional R&D activity and group-specific characteristics described above as independent variables. The parameters are estimated according to algorithm 2 of Simar and Wilson (2007), with 2000 bootstrap replications for the bias correction and 2000 bootstrap replications for the confidence intervals.

The estimation results are reported in Table 7. Given that the TTO groups considered in the first stage seem to perform differently, we identify them in the regression analysis. In particular, we introduce dummies for each group.

The results obtained in our second stage regression support the hypothesis that heterogeneity associated to different disciplinary fields impacts the TTOs efficiency. The impact (positive or negative) depends on the groups, as we expected. In particular, we find that ING and USC have some specific features which positively affect their performances while UPAM, UPSM and USHS/D-E have specific features which negatively impact the efficiency. This result confirms the classical wisdom about the technology transfer potential of medical sciences and engineering compared to other fields of research. It is also in line with findings in Siegel *et al.* (2008) and Caldera and Debande (2010).

Turning to the specific TTO characteristics, results reveal that the university TTO age appears to have a positive effect on efficiency in technology transfer. There is a learning process which takes place allowing an increased professionalization of the TTO staff members. This finding is in line with Mowery *et al.* (2001), Siegel *et al.* (2003) but in contrast with Chapple *et al.* (2005), Siegel *et al.* (2008) for US and UK TTOs, and partially with Caldera and Debande (2010). The university size contributes largely to the TTO efficiency. Measured by the number of professors employed at the university, the size indicates the potential transferable knowledge in terms of possible patentable results. This result suggests that universities with more researchers are likely to be more active and establish collaborative interactions to facilitate the technology transfer. This confirms the results obtained by Caldera and Debande (2010). Contrary to the previous positive effects found above, university-related hospital plays an important role in dampening the TTO efficiency. It confirms partially the results of previous studies (e.g. Thursby and Kemp, 2002; Chapple *et al.*, 2005), while contrasting with the findings in Siegel *et al.* (2003) and Siegel *et al.* (2008). However, in France, this negative effect is ascribed to an excessive "local competition" presumably concentrated on the medical school and the university-related hospital. Both institutions, the university and the university-related hospital, are legally independent entities. As a consequence, they both try and capture the potential technology transfers from life and medical sciences. Although our measures are partial and only the university side is counted, we are able to derive first insights on this aspect.

As far as the regional effects are concerned, there is a direct connection between R&D activity and TTO efficiency. Both Public and Private R&D Expenditure are found to have a positive impact on efficiency, with Private R&D Expenditure having the larger impact. This implies that the interaction between private firms and TTOs enhances the performance of the latter. This result is partially confirmed by the rate of growth of Private and Public R&D expenditure, as only the former seems to have a positive impact. The interpretation of these results is that the dynamics of technology transfer are essentially pulled from the 'outside'. This is in line with Siegel *et al.* (2003), Chapple *et al.* (2005), Siegel et al. (2008). On the contrary, while previous papers found the economic performance at regional level not to be significant (Siegel *et al.,* 2003, Siegel *et al.,* 2008), we find that there is a negative relation between the economic performance of the region where the TTO is located and the TTO itself. Our results reveal that the R&D dimension of the regional economic activities matters particularly when at the macroeconomic level the regional general activities are weak.

Our results show in fact the coexistence of the two simultaneous effects of the technology transfer process: a push effect from the university and a pull effect from the private industrial sector, which simultaneously have a positive impact, enhancing the efficiency of French TTO technology process.

7 Conclusions

This is the first attempt to study the efficiency of the technology transfer operated by the French university system since the major reforms of the early 2000 This study aims to contribute to the literature and the actual debate providing empirical evidence on an original and detailed dataset built by the BETA (University of Strasbourg) on French TTOs over the period 2003-2007. TTOs' performance and relative determinants are deeply investigated in several dimensions ranging from specific to group characteristics, from economic to R&D activity conditions in the region where the TTO is located.

Our analysis is based on a two-stage DEA using bootstrap techniques to provide statistical inference on the main drivers of TTOs efficiency. As an innovation in the field of TTOs performance, we carefully account for possible sources of efficiency heterogeneity not only between groups but also within groups.

In the first stage of the analysis, we find substantial inefficiency across French TTOs and in the system as a whole. Moreover, we find that TTO efficiency differs systematically according to disciplinary fields. In particular, results indicate higher technical efficiency on average among ING and USC TTOs while USHS/D-E and UPSM rank at the bottom. The confidence interval analysis of the individual TTO efficiency (as innovative methodological approach to this field of literature) highlights the presence of "hidden" heterogeneity, this time, within each group of universities. While the first form of heterogeneity is more related to the nature of the disciplinary field, the "hidden" one might be ascribed to several aspects. For instance, these results may suggest that outputs used in our production models do not cover the full range of TTOs activities. Commercialization via patents and licenses is certainly a particular way for public research institutions to contribute to the economy. But there are also other ways to collaborate and to transfer knowledge. There are formal interactions, such as contract research, public-private partnerships, collaborative research, service deliveries, consultancies and informal interaction, such as advice and networking, expertise and cultural activities. However, our analysis focuses on the TTO efficiency and mostly on the formal interactions, such as patents related activities, that are usually handled by TTOs and represent in many cases a great part of their activity.

In the light of first stage results, at the second stage we statistically investigate the link between TTO performance and relevant aspects to the technology transfer process operated by TTOs. These are related to specific- and group- characteristics as well as economic conditions of the regions where TTOs are located.

The analysis confirms that some categories of universities, namely universities in engineering, natural science and polyvalent with medical school have some specific features which affect positively the performance of their TTOs. Further, the analysis confirms that multiple affiliations such as medical school and a university-related hospital are certainly a source of inefficiency due to the excessive competition among locally close TTOs. Regarding additional specific TTO characteristics, we find that seniority of TTOs (particularly when the technology transfer function was introduced before 1999) has a positive impact. Moreover, it is also found that the well-functioning French TTO is driven by two forces: the scale economies related to the university size, on the one hand, and the local intensity of industry (and public) R&D on the other. This implies that TTOs could enhance their efficiency when these two forces work simultaneously.

Further investigations will be directed to including in the analysis more recent years, additional outputs to proxy also the informal channels of technology transfer and to take into account the influence of outliers in the explanation of inefficiency determinants by applying the recently developed nonparametric conditional methodology (Daraio and Simar, 2007; Daraio, Simar and Wilson, 2010; Badin, Daraio and Simar, 2011).

Acknowledgements

This paper was presented at the Conference «Knowledge in space and time: economic and policy implications of the Knowledge-based economy », April 7th-9th, 2008 BETA, University Louis Pasteur, Strasbourg, and at the “R&D, Science, Innovation and Intellectual Property” International Conference in Honor of Jacques Mairesse, ENSAE, Paris, September 16th–17th, 2010.We thank conference participants for their comments and suggestions. We thank for their support on handling the database EcS-BETA and Aquameth Gabrielle Genet, Karine Pellier from the University of Strasbourg. A special acknowledgment to Laurent Bach for the data collection under the three campaigns ‘Valo 1, 2 and 3’. Patrick Llerena acknowledges also for financial support over the years: the French Ministry in charge of Higher Education and Research, the Network of Excellence DIME, the project AnCoRA funded by the A.N.R. The usual disclaimers apply.The usual disclaimers apply.

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Tables of the paper

Table 1: Selected results from the literature on TTOs efficiency.

TTOs	Number of outputs	Authors	Output used	MED	AGE	INC	SCI	PUB	SIZE	GROUP[9]	REG GDP	REG R&D
US	One output	Siegel et al. 2003 Anderson et al. 2007	Number of licences	ne	ne			ne			ne	+
			Licensing Income	no	+			ne			ne	ne
	Multiple output	Thursby and Kemp 2002	Number of licenses, patent applications, invention disclosures, amount of royalties and industry sponsored research	-				+[10]		yes		
UK	One output	Chapple et al. 2005	Number of licences	ne	+						ne	+
			Licensing Income	-	ne						+	ne
Spain	One ouput	Caldera and Debande 2010	Number of licences	ne	ne		ne	-	+	ne		
			Licensing Income	ne	+		+	ne	+	+		
US & UK	Multiple output	Siegel et al. 2008	Number of licenses, income from licenses, university startups	+	-	+	ne				ne	+

Note 1: "ne" stands for no effect, "+ " for positive effects, "-" for negative effects, "yes" means that there is an impact and it depends on what we control for.

Note 2: MED stands for Medical School, AGE for TTO Age, INC for Incubator, SCI for Science Park, PUB for Public University, SIZE for University Size, GROUP for Group Characteristics, REG GDP for Regional GDP and REG R&D for Regional R&D.

[9] This effect is controlled using different approaches.
[10] In this case, authors test whether (or not) a private university effect the TTO performance.

Table 2: Descriptive Statistics by TTOs categories

Class	*Variable*	*ETP*	*PUB*	*PAT_APP*	*SW_APP*	*PAT_EXT*	*Nb_PAT_EXT*
ING	Mean	6.197	661.105	3.629	1.303	0.810	2.667
	Median	2.500	737.461	3.000	0.000	0.000	1.000
	St.Dev.	6.496	398.331	3.734	2.801	1.504	3.851
	Min	0.500	52.741	0.000	0.000	0.000	0.000
	Max	26.650	1463.830	15.000	15.000	5.000	16.000
UPAM	Mean	5.173	783.978	4.083	0.820	1.868	1.974
	Median	4.000	723.696	3.000	0.000	1.000	1.000
	St.Dev.	4.709	354.676	3.665	1.385	2.133	2.194
	Min	1.500	0.000	0.000	0.000	0.000	0.000
	Max	26.650	1701.007	19.000	6.000	8.000	9.000
UPSM	Mean	2.639	357.671	1.474	0.345	0.436	0.718
	Median	2.000	224.847	1.000	0.000	0.000	0.000
	St.Dev.	1.686	319.849	2.458	0.965	1.334	1.555
	Min	0.000	51.567	0.000	0.000	0.000	0.000
	Max	7.000	1405.848	12.000	6.000	7.000	7.000
USC	Mean	11.662	2757.143	10.000	1.869	5.714	6.452
	Median	9.700	2511.680	8.000	1.000	4.000	6.500
	St.Dev.	8.670	1779.189	8.118	2.802	5.518	5.388
	Min	2.000	88.733	0.000	0.000	0.000	0.000
	Max	39.000	7664.471	40.000	12.000	18.000	18.000
USHS/D-E	Mean	3.180	45.779	0.150	0.600	0.083	0.083
	Median	2.000	30.146	0.000	0.000	0.000	0.000
	St.Dev.	2.997	48.016	0.489	0.883	0.289	0.289
	Min	1.000	1.000	0.000	0.000	0.000	0.000
	Max	11.000	140.983	2.000	3.000	1.000	1.000

Source: Authors calculations

Table 3: Correlation coefficients

	ETP	PUB	PAT _APP	SW_APP	PAT_EXT	Nb_PAT_EXT
ETP	1					
PUB	0.7833	1				
PAT _APP	0.7541	0.8321	1			
SW_APP	0.374	0.2841	0.466	1		
PAT_EXT	0.6258	0.733	0.8787	0.3966	1	
Nb_PAT_EXT	0.6747	0.7479	0.88	0.3709	0.9292	1

Source: Authors calculations

Table 4: Descriptive Statistics by categories of universities

Class	*Variable*	*AGE*	*SIZE*	*HOSPITAL*
ING	Mean	11.743	988.171	0.000
	Median	9.000	1072.000	0.000
	St.Dev.	9.160	465.108	0.000
	Min	0.000	436.000	0.000
	Max	28.000	1768.000	0.000
UPAM	Mean	7.923	923.692	0.923
	Median	8.000	850.000	1.000
	St.Dev.	3.124	619.429	0.277
	Min	2.000	410.000	0.000
	Max	14.000	2878.000	1.000
UPSM	Mean	4.569	1229.725	0.000
	Median	4.000	922.000	0.000
	St.Dev.	2.727	759.309	0.000
	Min	0.000	102.000	0.000
	Max	11.000	2700.000	0.000
USC	Mean	15.214	1181.500	0.750
	Median	16.000	1095.000	1.000
	St.Dev.	8.437	640.715	0.500
	Min	0.000	281.000	0.000
	Max	37.000	2286.000	1.000
USHS/D-E	Mean	4.250	1389.400	0.000
	Median	3.500	1470.000	0.000
	St.Dev.	3.193	489.197	0.000
	Min	0.000	624.000	0.000
	Max	11.000	1980.000	0.000

Sources: Age: Bach and Llerena 2006-2008-2010; Size: Aquameth-PRIME NoE database, all other variables: OST, 2008 and 2010.

Table 5: Efficiency Estimates by university category, Model 1.

University Type	Efficiency Estimate (EFF)	Efficiency Estimate Bias-corrected (C-EFF)	Estimated bias (Est-Bias)	Estimated Std (Est-Std)	Confidence Interval: lower bound (LB)	Confidence Interval: upper bound (UB)
ING-9	1.099	1.271	-0.172	0.074	1.118	1.408
ING-30	1.000	1.317	-0.317	0.129	1.037	1.531
ING-3	1.000	1.325	-0.325	0.130	1.034	1.531
ING-24	1.224	1.515	-0.291	0.116	1.270	1.719
ING-35	1.416	1.587	-0.171	0.085	1.442	1.762
ING-36	1.734	2.104	-0.370	0.157	1.789	2.400
ING-32	7.036	8.023	-0.987	0.476	7.138	8.975
Geom. Mean	1.567	1.902				
Std.Dev.	2.204	2.474				
UPAM-14	1.000	1.249	-0.249	0.086	1.036	1.385
UPAM-23	1.000	1.309	-0.309	0.119	1.031	1.486
UPAM-31	1.086	1.345	-0.259	0.121	1.122	1.571
UPAM-22	1.112	1.365	-0.253	0.116	1.145	1.580
UPAM-21	1.426	1.763	-0.338	0.151	1.478	2.041
UPAM-50	1.592	1.867	-0.275	0.113	1.633	2.078
UPAM-55	2.018	2.328	-0.310	0.136	2.069	2.594
UPAM-18	2.049	2.454	-0.405	0.167	2.121	2.771
UPAM-2	2.056	2.585	-0.529	0.230	2.115	3.016
UPAM-41	2.145	2.611	-0.466	0.217	2.199	3.029
UPAM-7	2.356	2.622	-0.267	0.148	2.378	2.935
UPAM-71	2.607	2.883	-0.276	0.157	2.637	3.222
UPAM-59	3.742	4.677	-0.935	0.436	3.875	5.460
Geom. Mean	1.719	2.078				
Std.Dev.	0.787	0.939				
UPSM-25	1.000	1.280	-0.280	0.121	1.033	1.492
UPSM-4	1.000	1.384	-0.384	0.172	1.030	1.651
UPSM-49	1.000	1.444	-0.444	0.235	1.029	1.867
UPSM-10	1.255	1.579	-0.325	0.155	1.289	1.866
UPSM-43	1.453	1.700	-0.247	0.107	1.488	1.913
UPSM-12	1.643	2.044	-0.401	0.156	1.702	2.311
UPSM-61	2.026	2.248	-0.223	0.119	2.056	2.505
UPSM-1	2.193	2.615	-0.422	0.219	2.252	3.062
UPSM-17	2.702	3.346	-0.644	0.292	2.794	3.870
UPSM-62	4.549	5.721	-1.172	0.515	4.689	6.721
UPSM-52	5.619	6.461	-0.842	0.386	5.724	7.239
UPSM-38	6.369	7.662	-1.292	0.498	6.567	8.627
UPSM-74	8.225	10.737	-2.512	1.428	8.412	13.401
Geom. Mean	2.292	2.856				
Std.Dev.	2.396	2.998				

University Type	Efficiency Estimate (EFF)	Efficiency Estimate Bias-corrected (C-EFF)	Estimated bias (Est-Bias)	Estimated Std (Est-Std)	Confidence Interval: lower bound (LB)	Confidence Interval: upper bound (UB)
USC-68	1.000	1.271	-0.271	0.121	1.033	1.498
USC-73	1.000	1.320	-0.320	0.126	1.034	1.530
USC-69	1.000	1.320	-0.320	0.138	1.038	1.563
USC-34	1.000	1.328	-0.328	0.149	1.028	1.591
USC-5	1.000	1.349	-0.349	0.143	1.022	1.565
USC-64	1.000	1.373	-0.373	0.162	1.034	1.626
USC-51	1.211	1.392	-0.181	0.076	1.250	1.544
USC-33	1.306	1.543	-0.238	0.101	1.344	1.748
USC-42	1.627	1.940	-0.313	0.151	1.683	2.235
USC-26	1.582	1.942	-0.361	0.156	1.636	2.249
USC-37	1.893	2.300	-0.407	0.183	1.947	2.647
USC-65	2.490	3.001	-0.512	0.224	2.562	3.437
USC-54	3.444	4.097	-0.654	0.319	3.538	4.720
USC-13	3.960	4.645	-0.685	0.284	4.066	5.214
Geom. Mean	1.488	1.857				
Std.Dev.	0.967	1.101				
USHS/DE-58	1.000	1.442	-0.442	0.233	1.028	1.867
USHS/DE-48	1.000	1.446	-0.446	0.230	1.039	1.867
USHS/DE-60	2.044	2.635	-0.592	0.272	2.117	3.138
USHS/DE-46	7.515	9.469	-1.954	0.838	7.717	11.000
Geom. Mean	1.980	2.686				
Std.Dev.	3.123	3.855				
Overall Geom. Mean	1.775	2.202				
Overall Std. Dev.	1.803	2.201				

Source: Authors calculations

Table 5: Efficiency Estimates by category, Model 1 (cont.)

Table 6: Efficiency Estimates by category, Model 2.

University Type	Efficiency Estimate (EFF)	Efficiency Estimate Bias-corrected (C-EFF)	Estimated bias (Est-Bias)	Estimated Std (Est-Std)	Confidence Interval: lower bound (LB)	Confidence Interval: upper bound (UB)
ING-30	1.000	1.300	-0.300	0.131	1.026	1.516
ING-9	1.099	1.340	-0.241	0.115	1.119	1.533
ING-3	1.000	1.340	-0.340	0.146	1.028	1.557
ING-36	1.000	1.355	-0.355	0.160	1.025	1.582
ING-35	1.000	1.395	-0.395	0.208	1.031	1.741
ING-24	1.224	1.525	-0.302	0.129	1.261	1.755
ING-32	7.036	8.045	-1.009	0.495	7.146	9.038
Geom. Mean	1.379	1.769				
Std.Dev.	2.263	2.522				
UPAM-18	1.000	1.256	-0.256	0.129	1.032	1.491
UPAM-31	1.000	1.269	-0.269	0.118	1.027	1.477
UPAM-23	1.000	1.342	-0.342	0.152	1.030	1.568
UPAM-14	1.000	1.352	-0.352	0.156	1.026	1.557
UPAM-22	1.112	1.383	-0.270	0.123	1.147	1.600
UPAM-21	1.179	1.480	-0.301	0.136	1.206	1.713
UPAM-50	1.592	1.938	-0.346	0.173	1.629	2.248
UPAM-55	2.018	2.337	-0.320	0.144	2.069	2.618
UPAM-2	2.056	2.572	-0.516	0.234	2.118	3.020
UPAM-7	2.356	2.610	-0.255	0.148	2.376	2.932
UPAM-41	2.145	2.668	-0.522	0.246	2.191	3.077
UPAM-71	2.607	2.944	-0.337	0.182	2.646	3.312
UPAM-59	2.558	3.151	-0.593	0.265	2.636	3.646
Geom. Mean	1.547	1.908				
Std.Dev.	0.645	0.711				
UPSM-25	1.000	1.322	-0.322	0.137	1.029	1.525
UPSM-17	1.000	1.326	-0.326	0.142	1.026	1.546
UPSM-10	1.062	1.351	-0.289	0.127	1.087	1.571
UPSM-4	1.000	1.389	-0.389	0.193	1.022	1.687
UPSM-49	1.000	1.413	-0.413	0.227	1.028	1.858
UPSM-12	1.143	1.435	-0.291	0.129	1.175	1.656
UPSM-43	1.438	1.786	-0.348	0.152	1.481	2.059
UPSM-61	2.026	2.244	-0.219	0.122	2.057	2.524
UPSM-38	1.841	2.265	-0.424	0.236	1.877	2.723
UPSM-1	2.193	2.630	-0.437	0.230	2.230	3.093
UPSM-62	4.549	5.692	-1.143	0.522	4.681	6.717
UPSM-52	5.619	6.439	-0.819	0.401	5.690	7.205
UPSM-74	8.225	10.543	-2.318	1.399	8.387	13.413
Geom. Mean	1.851	2.336				
Std.Dev.	2.263	2.807				

University Type	Efficiency Estimate (EFF)	Efficiency Estimate Bias-corrected (C-EFF)	Estimated bias (Est-Bias)	Estimated Std (Est-Std)	Confidence Interval: lower bound (LB)	Confidence Interval: upper bound (UB)
USC-68	1.000	1.265	-0.265	0.128	1.029	1.494
USC-34	1.000	1.316	-0.316	0.152	1.033	1.602
USC-5	1.000	1.332	-0.332	0.146	1.030	1.560
USC-69	1.000	1.342	-0.342	0.154	1.028	1.593
USC-73	1.000	1.347	-0.347	0.161	1.023	1.603
USC-64	1.000	1.367	-0.367	0.174	1.024	1.630
USC-51	1.211	1.422	-0.211	0.091	1.251	1.591
USC-37	1.182	1.463	-0.280	0.141	1.222	1.740
USC-33	1.305	1.582	-0.277	0.117	1.340	1.803
USC-42	1.315	1.626	-0.311	0.143	1.355	1.902
USC-26	1.386	1.721	-0.336	0.143	1.438	1.982
USC-65	2.490	3.077	-0.588	0.260	2.558	3.533
USC-54	3.444	4.100	-0.656	0.332	3.542	4.741
USC-13	3.829	4.603	-0.774	0.310	3.940	5.176
Geom. Mean	1.437	1.815				
Std.Dev.	0.978	1.138				
USHS/DE-58	1.000	1.400	-0.400	0.223	1.033	1.854
USHS/DE-48	1.000	1.413	-0.413	0.222	1.037	1.855
USHS/DE-60	2.044	2.600	-0.557	0.271	2.097	3.110
USHS/DE-46	2.926	3.697	-0.771	0.407	2.977	4.430
Geom. Mean	1.564	2.088				
Std.Dev.	0.930	1.101				
Overall Geom. Mean	1.553	1.961				
Overall Std. Dev.	1.537	1.836				

Table 5: Efficiency Estimates by category, Model 2 (cont.)

Table 7: Determinants of (in-) efficiency differentials

(Truncated, bootstrapped second-stage regression, inefficient score)

Variables		CI-90%		CI-95%		CI-99%	
	Estimates	LB	UB	LB	UB	LB	UB
Age	-0.128*	-0.170	-0.078	-0.207	-0.023	-0.330	0.183
Size	-4.843***	-5.370	-4.210	-5.781	-3.888	-7.589	-3.186
Regional GDP	1.644***	1.406	1.914	1.173	2.165	0.637	2.745
Regional Public R&D Expenditure	-0.437**	-0.509	-0.310	-0.612	-0.178	-0.929	0.202
Regional Private R&D Expenditure	-2.091**	-2.597	-1.668	-2.880	-1.443	-3.885	-0.834
Growth Rate Regional GDP (%)	0.020**	0.016	0.022	0.012	0.026	-0.009	0.036
Growth Rate Public R&D Expenditure (%)	0.041**	0.033	0.046	0.026	0.049	-0.002	0.075
Growth Rate Private R&D Expenditure (%)	-0.402***	-0.427	-0.382	-0.444	-0.382	-0.535	-0.365
H	5.644***	4.739	6.070	4.427	6.749	3.455	9.072
ING	-0.259***	-0.326	-0.150	-0.407	-0.045	-0.738	0.493
UPAM	0.684**	0.536	1.094	0.377	1.431	-0.368	2.185
UPSM	8.233***	6.792	9.985	6.322	11.019	5.686	13.380
USC	-0.019*	-0.025	-0.010	-0.033	0.000	-0.056	0.024
USHS	13.940***	11.951	16.114	11.574	17.100	10.616	20.010
σ_{ε}^{2}	4.939***	4.802	5.401	4.657	5.760	3.978	6.667

Notes:
*=statistically significant at 90%
**= statistically significant at 95%
***= statistically significant at 99%
Note: The variables Public and Private expenses in R&D are highly correlated. Therefore the model has been estimated using these variables one at time.

Figures of the paper

Figure 1: Definition of TT production process of a TTO

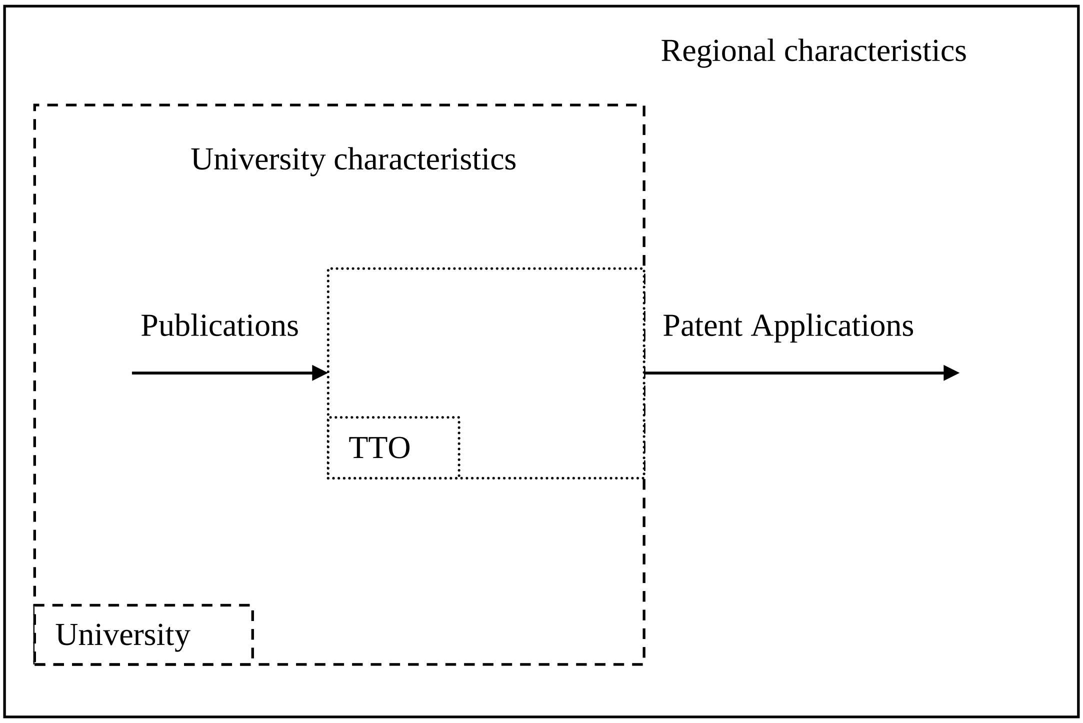

Figure 2: Boxplots of bias-corrected efficiency scores by category.Model 1(left panel) and Model 2 (right panel)