

Assessing the technology transfer productivity of universities: An analysis of the relevance of portfolio complexity in technology transfer offices

Esteban Lafuente¹

Department of Management, Universitat Politècnica de Catalunya (Barcelona Tech)
EPSEB, Av. Gregorio Marañón, 44-50, 3era planta. 08028. Barcelona. Spain
Email: esteban.lafuente@upc.edu

Jasmina Berbegal-Mirabent

Department of Economy and Business Organization, Universitat Internacional de Catalunya
C. Immaculada, 22. 08017. Barcelona, Spain
Email: jberbegal@uic.es

Abstract:

The paper investigates the technology-transfer productivity of Spanish public universities. The proposed approach allows the development of a framework that matches universities' technology transfer concerns with the need to accurately analyze the role of the outcome configuration of technology transfer offices (TTOs). We analyze technology transfer productivity of Spanish universities during 2006-2011 by computing total factor productivity models rooted in non-parametric techniques, namely the Malmquist index. The results confirm that technology transfer productivity is affected by changes in the configuration of the TTO's outcome portfolio that result from benchmarking own and market peers' performance levels. While benchmarking own performance levels facilitates the exploitation of internal resources and yields superior productivity results, changes in TTO's portfolio based on comparisons with market peers might generate greater operational costs that negatively impact productivity.

Keywords: Technology transfer, universities, total factor productivity, data envelopment analysis, aspiration performance

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¹ Corresponding author

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1. Introduction

Universities are organizations that perform a key role within contemporary societies by educating large proportions of the population and generating various forms of valuable knowledge. Recently, often on the initiative of policy-makers, many universities have taken action to develop a ‘third mission’ by fostering links with knowledge users and facilitating technology transfer (Dill, 2014; Etzkowitz et al., 2000; Gulbrandsen and Slipersæter, 2007).

Governments have traditionally channeled considerable resources to finance scientific outcomes and technology transfer activities, either through tax policy or direct investment. Additionally, the growing awareness of the importance of universities as key pillars for the consolidation of knowledge-based economies has led European governing bodies to adopt specific policies within the EU 2020 strategic plan aimed at stimulating knowledge creation and diffusion, as well as scientific productivity among universities (European Commission, 2015).

The increased emphasis on the commercialization of technology transfer outcomes to the private sector has led many universities to create Technology Transfer Offices (TTOs). TTOs can be seen as knowledge brokers that encourage technology transfer processes from academia to industry by bringing together scientists, businesses and venture capitalists (Anderson et al., 2007; Caldera et al., 2010; Friedman and Silberman, 2003; Sellenthin, 2009). Nevertheless, universities do not realize the generally positive effects of TTOs at the same intensity. From an organizational perspective, TTOs are challenged with the need to harmonize scientists’ interests—who often prioritize their scientific productivity—with the exploitation of their resources to transfer the new knowledge generated within the university to the industry.

At the university level, the success of technology transfer activities is conditioned by the work of the TTO. A common presumption is that TTOs must maximize their technology transfer outcomes (i.e., spinoffs, licenses, patents). Yet, different resources, abilities and internal processes are necessary to generate technology transfer outcomes; and TTOs’ performance might be affected by resource allocation policies and by strategic choices linked to the TTO’s outcome portfolio that are not necessarily conducive to technology transfer outputs. This is the focus of this study.

More concretely, this study evaluates the technology transfer productivity of Spanish universities via total factor productivity models rooted in non-parametric techniques (Data Envelopment Analysis, DEA). Additionally, we explore the role on productivity of strategic choices linked to changes in the configuration of the TTO’s technology transfer portfolio based on the benchmarking of own and other TTOs performance levels.

The empirical application considers the Spanish public university system between 2006 and 2011. This setting is attractive because, similar to other European countries, Spain has undergone significant reforms in the university's regulatory framework seeking to parameterize technology transfer outcomes and enhance publicly funded technology transfer activities. This implies drastic modifications in the universities' strategic model in which TTOs play a key role. The Spanish setting offers the opportunity to analyze how TTOs capitalize on their resources seeking to produce technology transfer outcomes in a context in which information availability gives TTOs strong incentives to benchmark their own and other TTOs and introduce changes that might enhance their productivity levels.

The remainder of the paper is organized as follows. Section 2 presents the theoretical underpinning. Section 3 describes the main characteristics of the Spanish university system. Section 4 describes the data and the methodological approach. Section 5 offers the empirical results, and Section 6 provides the discussion, implications and concluding remarks.

2. Theory

2.1 Knowledge generation and the reconciling role of technology transfer offices

Universities have different goals. In addition to the traditional academic- and research-oriented objectives, in recent decades the universities' role have witnessed a major change and they are now submitted to new challenges as society advances in science and technology (Dill, 2014). In this context, many voices have claimed for a deeper involvement of universities with various stakeholders via a closer association between industry and science (Perkmann et al., 2013). The universities' third mission—interaction with surrounding stakeholders—implies the provision of new knowledge, experience and technological solutions to industry demands. Furthermore, universities are called to actively interact with society through the development of activities with potentially positive territorial economic effects (Schattock, 2009).

University research can spur business innovation, foster competitiveness, and promote economic and social development (Algieri et al., 2013). The institutional changes underwent by universities have increased the incentives to remain at the cutting-edge of research, recruit highly skilled human capital, and develop appropriate mechanisms and infrastructures to accelerate the valorization process of knowledge. Accordingly, there is a growing body of research assessing the drivers and outcomes of universities' technology transfer efforts (Agasisti and Wolszczak-Derlacz, 2015; Anderson et al., 2007; Baldini, 2009; Berbegal-Mirabent et al., 2013; Caldera and Debande, 2010; Clarysse et al., 2005; Feldman et al., 2002; Hsu et al., 2015; Kim, 2013; Rasmussen et al., 2006; Thursby and Thursby, 2002).

Knowledge is disseminated and commercialized in the form of scientific publications, license contracts or patents. Research outcomes can also be the starting point for the creation of a new venture. Technology transfer activities and scientific excellence are mutually reinforcing

(Baldini, 2006); however, previous studies show that this process has taken place at different rates and intensities (Shattock, 2009), and that these transformations are highly tied with the strategic vision of each university. Although the increased usability of university innovations by industry (Kim, 2013), it is widely acknowledged that the commercialization of knowledge generated within universities is hard, and that certain discrepancies between universities and industry might affect this process.

First, universities and industry have different objectives. While market-oriented firms prioritize research low in riskiness with direct marketability, public universities mostly focus on the development of projects with a longer time horizon and uncertain commercial applications (Di Gregorio and Shane, 2003). Second, a discrepancy exists on how to capitalize new knowledge. Scholars mostly facilitate the diffusion of new knowledge as a public good by fully disclosing work methods and results linked to the new knowledge. On contrary, businesses seek to secure the control of intellectual property and the potential future rents resulting from the new knowledge. Additionally, scientists have strong incentives to share their research as quickly as possible via scientific publications, while the industry is interested in delaying the publication process to keep scientific results with potential economic value hidden (Anderson et al., 2007).

Third, prior research shows that scientists' dissimilar involvement in technology transfer activities might result from a weak system of incentives (Vinig and Lips, 2015). Universities often evaluate faculty on the basis of systems that link a successful academic career to valuable research accomplishments, which sways scholars to produce academically rigorous research and develop research networks (Shane, 2002). Thus, many scientists lack the skills and abilities to engage in commercial activities, which limit their capacity to create or develop university-industry collaborations (Perkmann and Walsh, 2009), and might explain the highly skewed distribution of successful commercialization among universities (Vinig and Lips, 2015).

The increased emphasis on transferring technology to the private sector for commercialization as an economic strategy has led many universities to create Technology Transfer Offices (TTOs) to legitimize their commercial activities (Friedman and Silberman, 2003). Starting in the US in the 1980s but rapidly expanding to other countries, TTOs have been included in universities' organizational structure or established as independent structures outside the university but operating in its name (Algieri et al., 2013). TTOs are knowledge brokers that bring together academics, businesses and venture capitalists, and seek to facilitate the transfer of knowledge from academia to industry. The role of TTOs mostly consists of spreading an entrepreneurial culture of research, encourage the dissemination of scientific outcomes and support scholars through the stages of research commercialization (Caldera et al., 2010). Also, by employing its resources to build strong networks the TTO contributes to reduce barriers between scientists and industry (Friedman and Silberman, 2003).

A growing literature stream on TTOs has evaluated why some universities are more successful than others in commercializing research outcomes (see e.g., Anderson et al., 2007; Rasmussen et al. 2006; Wright et al. 2007). Results are inconclusive. Notwithstanding the diverse and complex attributions of TTOs complicate the creation of accurate metrics to capture their performance (Hsu et al., 2015; Perkman et al., 2013), it seems that organizational practices and resource allocation strategies explain a significant proportion of the variation in technology transfer performance (Anderson et al., 2007; Balsmeier and Pellens, 2014; Siegel et al., 2007).

Within universities, scientists are the suppliers of valuable and potentially marketable knowledge. The transfer of knowledge and technology from university to industry appears in a myriad of forms that include formal (i.e., patents, R&D contracts, licenses, spin-offs) and informal (i.e. personal contacts, industry-science networks, cooperation in education) outcomes.

From an organizational perspective, the biggest challenge for TTOs is to harmonize the elements of their production function, including scientists—who often pursue scientific productivity—and their unit-specific resources—i.e., staff specialized in knowledge-transfer activities and administrative support staff—to effectively exploit the knowledge generated within the university. Underlying prior research analysis is the assumption that TTOs must maximize their technology transfer outcomes (Anderson et al., 2007). Nevertheless, different resources, abilities and internal processes are necessary to produce the various TTO outcomes; and TTOs' performance might be affected by both the allocation of resources and strategic choices that are not directly conducive to the TTO outputs.

In a context where strategic choices condition TTOs' performance, variations in the configuration of the TTO's portfolio might result from the benchmarking of the TTOs-own' historical performance as well as other TTOs' actions. The policy significance of this issue lies in the need to gain insights into the value of the TTOs' outcomes currently being pursued by the exploitation of their resources. Such outcomes are the consequence of TTO's efforts for encouraging technology transfer outcomes in the expectation of the benefits that will accrue to both academia and industry. Given the ambiguous results in the literature, it seems worthwhile to investigate the conditions under which TTOs generate these benefits.

2.2 Aspiration performance and the strategic choices of technology transfer offices (TTOs)

The success of university technology transfer depends heavily on the work of the TTO. In the case of TTOs, the efficient commercialization of inventions requires high specific investments, the creation of efficient organizational structures and the recruiting of highly skilled staff. But, do TTOs strive for enhanced performance? Do decision-makers evaluate the TTO's success or failure by benchmarking their own past records or other peers in the university sector?

Existing research specifically addressing technology transfer performance has mostly analyzed the effect of variables linked to university inputs (e.g., university size and experience, faculty, research orientation of the university) and various factors related to the TTO (e.g., staff, budget, and experience) (Berbegal-Mirabent et al., 2013; Chapple et al., 2005; Sellenthin, 2009; Siegel et al., 2003; Thursby and Kemp, 2002; Vinig and Lips, 2015).

Nevertheless, the analysis of the relationship between benchmarking activities, changes in the strategic orientation of the TTO and technology transfer performance remains unaddressed. Building on insights from organizational theory, organizational change is primarily driven by discrepancies between the organization's performance aspirations and the feedback it receives in terms of its performance (Baum and Dahlin, 2007; Levitt and March, 1988). Performance-feedback theorists argue that businesses initiate change when they are dissatisfied with their expected or aspired-to performance level. An aspiration level is a reference point that simplifies performance evaluation by transforming business-specific outcome metrics into more informative measures of success or failure.

Aspiration levels arise from comparisons against two reference points that decision makers use to evaluate their own current performance: the organization's own historical performance (Levinthal and March, 1981) and performance of the organization's peer group (Baum and Dahlin, 2007; Labianca et al., 2009).

By definition, TTOs are catalysts of change and innovation. In the context of this study, all universities carry out different technology transfer activities; however, resources are unevenly allocated across TTOs and, consequently, TTOs' performance is also heterogeneous across universities. Different patterns are observed based on the relative importance given to the different components of universities' objective function in which technology transfer is critical. In this setting, the performance aspirations of publicly funded TTOs are more linked to the deepening of their technology transfer outputs and the rapid commercialization of their innovations, rather than economic results derived from short-term projects. Therefore, it seems plausible to argue that TTOs cater to the tastes of industry by fueling the market with value-adding innovations. Building on performance-feedback models (Chen and Miller, 2007; Levinthal and March, 1981), TTOs whose performance is below both own and market aspiration levels have strong incentives to introduce change in the configuration of their technology transfer portfolio seeking to enhance performance.

On contrary, can we expect that high-performing TTOs fall into complacency or inefficient inertia? Note that technology transfer activities are dynamic and highly competitive and that TTOs compete for attracting the attention of industries seeking to fund and commercialize their innovations. Also, TTOs whose performance is above their aspiration levels will likely enjoy a more solid organizational and financial position to engage in continuous change practices which makes it difficult for other TTOs to catch-up. This argument is at the

heart of competitive advantage theories that emphasize that innovativeness often provides the potential for the effective development of new products and services, significant changes in the organization's routines and practices, as well as changes in their strategies to compete in the market (Baum and Dahlin, 2007). Thus, according to this competitive advantage view, TTOs whose performance is above their aspiration levels will attempt to stay ahead of competitors by continuously diversifying their technology transfer activities as a way to consolidate their market position (Chen and Miller, 2007; Iyer and Miller, 2008).

Although in some contexts competitors' actions might remain hidden, Spanish TTOs must report their activity to the Network of Spanish Technology Transfer Offices (RedOTRI). Thus, the experience and final technology transfer outcomes of TTOs are visible, interpretable based on available information, and generalizable across universities. Moreover, because TTOs employ the same basic resources (specialized staff, infrastructures and networks) decision makers can gain access to valuable experience created by other publicly funded TTOs.

Taken together, these arguments and evidence suggest that TTOs whose performance is below their-own and market aspiration levels will engage in drastic change—in terms of their technology transfer portfolio—seeking to improve their performance, while TTOs with an above-aspiration performance will intensify and diversify their technology transfer activities to consolidate their competitive position.

3. Research context: Technology transfer in Spanish public universities

In Spain, the higher education system has gone through significant changes during the past decades. Before 2001, the Organic Law of Universities (LRU) 11/1983 was the legal framework regulating the hiring and contracting of university professors and researchers. This law grouped faculty in two main categories: permanent faculty (civil servants) and fixed-term faculty (non-civil servants). In 2001 a profound reform took place, and with the new Universities Act (LOU, 6/2001) in force universities enjoyed greater autonomy to restructure the processes through which academics are hired. Following the enactment of the 2001 Universities Act, the Spanish Government created in 2002 the Agency for Quality Assessment and Accreditation Trust (ANECA). This agency is the main authority within the higher education system, which evaluates and endorses the scientific activity of university researchers in Spain. The highly decentralized structure of Spain's institutions facilitated the creation of similar agencies with the same attributions in some regions (e.g., Catalonia and Galicia).

With the new regulatory frame governing universities in place, universities' research orientation is further emphasized, and the parameterization of technology transfer outputs facilitates the evaluation of both universities and academics. The primary objective of this evaluation process is to ensure that candidates for academic positions have an appropriate level of academic merit. The weight assigned to the various components of a CV (i.e. teaching

experience, research experience, educational background, and work experience) varies according to the teaching body (there are several categories), academic discipline and academic position. The higher the position, the more important are one's research credentials (i.e. publication history, research projects, technology transfer). Research experience typically accounts for at least half of the total score. Particularly, the number of papers published in academic journals is the most important criterion valued to accredit professors. Specifically, the weight of scientific publications in the final evaluation ranges between 26% and 35% (according to the knowledge filed). On the contrary, technology transfer outputs such as patents or spin-offs have a low impact, representing between 3% and 12% of the total evaluation score.

These imbalances on the weights assigned to basic and applied research outputs suggest that researchers' motivation to engage in the different types of technology transfer activities might differ based on their current contractual situation. For young academics and professors in a weaker contractual position, their academic career will be greatly determined by their capacity to publish their research. They have strong incentives to publish in order to create reputational signals that are expected to increase their probability to promote. To the contrary, full professors have no exogenous incentives to publish, and their only motivation is endogenously determined by their own interest in conducting research in their knowledge fields. Research conducted by full professors may be motivated by knowledge and technology transfer dissemination objectives, the enhancement or consolidation of research projects, or by reputational factors.

Concerning the technology transfer intensity of Spanish public universities, data from the Spanish Statistical Office (INE: www.ine.es) indicate that universities invested 3.6 billion euro on R&D in 2014, of which 39% (1.4 billion euro) came from market sources. Note that the universities' R&D budget represents 35% of their total budgeted (10.3 billion euro) in the same year. Also, figures show that the relevance of TTOs within the university system has grown. Information obtained from the Network of Spanish Technology Transfer Offices (RedOTRI: www.redotriuniversidades.net) reveals that 50% of the TTOs' budget came from the universities in 2011, while in 2014 this percentage stood at 58%. Private resources represented 22% of the TTOs budget in 2011, half of which was generated by university-industry collaboration projects. In 2014, university-industry collaboration projects represented 55% of the TTO's budget line referring to private funding which grew to 29% of the total TTOs' budget.

4. Data and methods

4.1 Data

The data used in this study come from two sources of information. First, we employ the reports provided by the Spanish Association of University Rectors (Conferencia de Rectores de Universidades Españolas, CRUE). The CRUE databases contain data on the faculty working in Spanish public universities. Also, this dataset comprises information about the publication

record of scientists of Spanish universities. Data on scientific publications included in these reports were gathered from the ISI Web of Science.

Second, all variables related to knowledge-transfer resources and outcomes were collected from the annual reports available from the Network of Spanish Technology Transfer Offices (RedOTRI). More concretely, from the RedOTRI reports we obtained detailed organizational data on the configuration of the employment in the technology transfer office (TTO), distinguishing between staff specialized in knowledge-transfer areas (business start-up process, design of licensing contracts, and intellectual property rights) and administrative support staff. Additionally, this database provides information on the number of spin-offs, licenses and patents generated by each university.

The database comprises information for all Spanish public universities from 2006 to 2011 (47 institutions). Yet, in the interest of following a rigorous methodology, three universities were excluded from the sample due to lack of reliable information (Universidad de Las Palmas, Universidad de León, Universidad Politécnica de Cartagena). Therefore, the final sample consists of 44 public universities for the period 2006-2011 (264 observations).

4.2 Efficiency analysis

When dealing with multiple inputs yielding multiple outputs, efficiency literature often makes use of data envelopment analysis (DEA) frontier methods (see, e.g., Cooper et al., 2011; Grifell-Tatjé and Lovell, 2015). DEA is a non-parametric technique that, through linear programming, approximates the true but unknown technology without imposing any restriction on the sample distribution. The primary technological assumption of DEA models is that production units (in our case, universities) (i) use a set of $\mathbf{x} = (x_1, \dots, x_J) \in \mathbb{R}_+^J$ inputs to produce a set of $\mathbf{y} = (y_1, \dots, y_M) \in \mathbb{R}_+^M$ outputs, and that these sets form the technology in the sector (T): $T = \{(\mathbf{x}, \mathbf{y}, t) : \mathbf{x} \text{ can produce } \mathbf{y} \text{ at time } t\}$. DEA is a complex benchmarking technique that yields a production possibilities set where efficient decision-making units positioned on this surface shape the frontier. For the rest of units DEA computes an inefficiency score indicating the units' distance to the best practice frontier.

The technology in DEA models has two properties that are worth defining. First, in this study the technology exhibits variable returns to scale (VRS) because pure technical efficiency measures (VRS) capture outcomes linked to practices undergone by decision makers in the short term (Chambers and Pope, 1996). The second assumption deals with the measurement orientation (input minimization or output maximization). The proposed DEA model maintains an output orientation. Business managers are often given output targets and told to produce them most efficiently, that is, with minimum inputs (Sengupta 1987, p. 2290). On contrary, in the public sector the workforce and assets tend to be fixed and policy-makers seek to produce

the maximal possible output given the resources available (Berbegal-Mirabent et al., 2013). The following linear program models the described technology and computes, for each university (i) and each period (t), the efficiency score via an output distance function ($D_i^t(x_i^t, y_i^t)$):

$$\begin{aligned}
D_i^t(x_i^t, y_i^t) &= \max \theta_i \\
\text{subject to } & \sum_{i=1}^N \lambda_i^t y_{i,m}^t \geq \theta_i y_{i,m}^t \quad m = 1, \dots, M \\
& \sum_{i=1}^N \lambda_i^t x_{i,j}^t \leq x_{i,j}^t \quad j = 1, \dots, J \\
& \sum_{i=1}^N \lambda_i^t = 1, \quad \lambda_i^t > 0 \quad i = 1, \dots, N
\end{aligned} \tag{1}$$

The drawn technology in equation (1) describes how universities transform their available resources (\mathbf{x} : faculty, TTO staff specialized in technology-transfer activities, and TTO administrative support staff)² into the maximum possible output (\mathbf{y} : spin-offs, licenses, and patents), uses λ as intensity weights to form the linear combinations of the sampled universities (N), and introduces the restriction $\sum_{i=1}^N \lambda_i^t = 1$ to impose variable returns to scale to the technology. The term θ is the efficiency score, and for efficient universities $\theta = 1$. For inefficient universities $\theta > 1$ and $1 - \theta$ points to the degree of inefficiency.

Next, the distance functions can be used to compute changes in total factor productivity (TFP) between two periods through the Malmquist index ($M(\cdot)$). The Malmquist TFP index were first introduced by Malmquist (1953) and has further been developed in the non-parametric framework by, among others, Caves et al. (1982), Färe and Grosskopf (1989) and Grifell-Tatjé and Lovell (1999). In a multiple input-output setting, this index reflects changes (progress or regress) in productivity along with changes (progress or regress) of the frontier technology over time.

In this study, the output-oriented Malmquist TFP index ($M_i(x_t, y_t, x_{t+1}, y_{t+1})$) is computed for each university (i) on the benchmark technologies in period t and $t+1$ as follows:

$$\begin{aligned}
M_i(x_t, y_t, x_{t+1}, y_{t+1}) &= \left[\frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)} \right] \times \left[\frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^t, y^t)} \right]^{0.50} \\
M_i(x_t, y_t, x_{t+1}, y_{t+1}) &= \Delta TE \times \Delta TC
\end{aligned} \tag{2}$$

The estimated TFP index distinguishes between the catch-up effect or the operating efficiency change (ΔTE)—variations in technical efficiency between periods t and $t+1$ —and the effect of technical change (ΔTC), that is, the shift in technology between the two periods (the geometric product of ratios inside the square brackets). Values greater than unity indicate

² It should be kept in mind that, during the analyzed period, reliable data on the TTO's budget are not available from the RedOTRI annual reports for 12 universities.

productivity growth (progress), while values lower than one point to decline (regress) between periods t and $t+1$. Analogous interpretations hold for the components of the TFP index.

As we indicated above, universities' productivity paths are evaluated under the premise that TTOs capitalize on their specific resources (faculty, TTO staff specialized in technology-transfer activities, and TTO administrative support staff) to maximize their technology-transfer outcomes (spin-offs, licenses, and patents).

Tables 1 and 2 present the descriptive statistics for the input-output set. Note that in our sample some TTOs report zero data values in the output set. More concretely, during the analyzed period nine universities report zero spin-offs, while five and two universities did not create any license or patent, respectively. Much has been said about how to handle 'badly behaved data' in DEA models (see, e.g., Thanassoulis et al., 2007). In fact, zero output values present no computational problems in DEA models and the estimated efficiency scores are technically feasible (Podinovski and Thanassoulis, 2007, p. 119). From an economic perspective, zero output values only point to the ineffective consumption of resources by a focal unit which translates into the production of zero outputs.³ Also, it is worth mentioning that in our dataset the output vector (\mathbf{y}) for all TTOs is positive ($\mathbf{y} > 0$) in all periods. Although some TTOs report zero values in some outputs, all TTOs in the sample report the production of at least one technology transfer output during the analyzed period (2006-2011).

----- Insert Tables 1 and 2 about here -----

4.3 Second stage analysis: The role of performance aspirations and portfolio configuration

The second stage analysis evaluates the relationship between productivity and aspiration performance among TTOs affiliated to public universities. To this end, note that we employ vector algebra to operationalize the portfolio of technology transfer outcomes. The complexity of the TTO's portfolio increases with the number of products in a given category (spin-offs, licenses and patents). Based on vector algebra, we undertook a pairwise comparison by calculating cosine values between the vectors of two TTOs (f_i, f_k) across all technology transfer outcomes (w) in the sector at period t .

$$\text{Configuration of TTO portfolio} = \frac{\vec{f}_i \cdot \vec{f}_k}{|\vec{f}_i| \times |\vec{f}_k|} = \frac{\sum_{i=1}^N w_i \times w_k}{\sqrt{\sum_{i=1}^N w_i^2} \times \sqrt{\sum_{i=1}^N w_k^2}} \quad (3)$$

³ Although it is not the case in our data, we extend the analysis to the case of zero values in the input set. Zero input values are problematic in DEA models. From an economic point of view, zero input values indicate that the focal unit can produce outputs without consuming resources, which leads to unfeasible DEA scores (see Thanassoulis et al. (2007) for a comprehensive review on this issue).

In equation (3), the vector of the number of products in each category (w) for each TTO (f_i) was compared to the vector of values of the rest of TTOs (f_k) in the same category. As the angle between the vectors shortens, the cosine value approaches 1 indicating that the vector of technology transfer outputs produced by the two TTOs is more similar.

For example, let's consider the case of a fictitious TTO (f_i) whose vector of outputs is [0,1,2], that is, the focal TTO does not produce any output in the first category (spin-offs), produces one output in the second category (licenses) and produces two products in the third category (patents). Similarly, for a reference TTO ($f_{k=1}$), the vector of outputs is [1,2,3].

Following equation (3), the cosine value for the comparison of the two TTOs is computed

as $\frac{8}{\sqrt{0+1+4} \times \sqrt{1+4+9}} = 0.96$. Now suppose a second reference TTO with a similar number

of outputs but with a different configuration [3,2,1]. In this case, the cosine value between the

focal TTO (f_i) and the reference TTO ($f_{k=2}$) is $\frac{4}{\sqrt{0+1+4} \times \sqrt{9+4+1}} = 0.48$. Although the

reference TTOs (f_{k1}, f_{k2}) have the same total number of outputs, the configuration of the output portfolio—based on the relative weight of each category in the output mix—of the focal TTO (f_i) is more similar to f_{k1} than f_{k2} .

Note that the proposed measure of portfolio configuration allows at differentiating three dimensions of TTO outputs: length (total output), breadth (categories), and depth (relevance of categories in the output mix based on the quantity of output in each category). In line with the arguments presented in section 2.2, this variable permits us to assess the extent to which TTOs benchmark their-own' and other TTOs' performance and how productivity is affected by strategic actions resulting from the analysis of TTOs' aspiration performance levels.

For each period, we measure the TTO-specific aspiration performance (AP^{TTO}) as the value of the configuration of the TTO portfolio minus its-own average value for the period prior the focal year of analysis. To allow for different slopes above and below aspiration levels, we split AP^{TTO} into two variables: 1) $AP^{TTO} > 0$ equals to zero for TTOs where performance is below their-own performance aspirations, and equals AP^{TTO} otherwise; 2) $AP^{TTO} < 0$ is zero for TTOs where performance is above their aspirations, and equals AP^{TTO} otherwise.

Likewise, for each TTO we defined the market aspiration level (AP^{MKT}) as the value of the configuration of the TTO portfolio minus the performance of other TTOs, that is, the average value of the configuration of the TTO portfolio for each period. Again, to permit different slopes for values above and below the aspiration level, we again split AP^{MKT} into two variables: 1) $AP^{MKT} > 0$ equals to AP^{MKT} for TTOs where performance is above market aspirations (and zero otherwise); 2) $AP^{MKT} < 0$ is zero for TTOs where performance is above market aspirations, and equals AP^{MKT} otherwise.

Additionally, we introduce a set of control variables commonly found in studies dealing with technology transfer performance (Agasisti and Wolszczak-Derlacz, 2015; Ambos et al., 2008; Chappel et al., 2005; Friedman and Silberman, 2003; Vinig and Lips, 2015; Wright et al., 2007). University size is measured by the total faculty, while university age is introduced as a proxy of market experience. The size and experience of the TTO is measured as the total staff and age, respectively. For both universities and TTOs, note that the variables related to size and experience are logged to reduce skewness. To account for the potential benefits derived from the presence of technology transfer intermediate organizations, we introduced a dummy variable taking the value of one if the university has a science parks, and zero otherwise. A dummy variable taking the value of one for polytechnic universities takes into account the potentially greater marketability of engineering-based inventions, compared to inventions from other disciplines. Finally, we include time dummies in all model specifications to rule out the potential effects of time trends and other environmental changes (in all models 2011 is the base year). Descriptive statistics for the study variables are presented in Table 3.

----- Insert Table 3 about here -----

We employ panel data techniques to estimate the proposed model which emphasizes a relationship between aspiration performance and universities' technology transfer productivity. Pooling repeated observations on the same organizations violate the assumption of independence of observations, resulting in autocorrelation in the residuals. First-order autocorrelation occurs when the disturbances in one time period are correlated with those in the previous time period, resulting in incorrect variance estimates, rendering ordinary least squares (OLS) estimates inefficient and biased (Wooldridge, 2002). Therefore, we estimate random-effects (GLS) panel data models with robust standard errors to correct for autocorrelation of error terms due to constant university-specific effects (Greene, 2003). Additionally, the proposed estimation approach allows at evaluating the effect of relevant time-invariant factors on technology transfer productivity. To evaluate the role of aspiration performance empirically we propose a random-effects model with the following form:

$$\begin{aligned} \text{TFP}_{it} = & \beta_0 + \beta_1 \text{AP}_{it}^{TTO} > 0 + \beta_2 \text{AP}_{it}^{TTO} < 0 + \beta_3 \text{AP}_{it}^{MKT} > 0 + \beta_4 \text{AP}_{it}^{MKT} < 0 \\ & + \beta_5 \text{Control variables}_{it} + \beta_6 T_t + \varepsilon_{it} \end{aligned} \quad (4)$$

In equation (4) TFP is the Malmquist TFP index computed from equation (2), β_j are parameter estimates estimated for the independent variables (j), ε is the normally distributed error term that varies cross-universities and cross-time (t), while T refers to the set of time dummy variables.

We estimated the Hausman (1978) specification test to further validate the appropriateness of the proposed regression models. Results for model 1 (Hausman test: 7.70 and p -value<0.56) and model 2 (Hausman test: 6.75 and p -value<0.82) indicate that random effects estimations are independent of university-specific effects—i.e., regressors are consistent—thus confirming that random-effects coefficients are consistent and efficient (Wooldridge, 2002).

5. Results

5.1 *Technology transfer productivity of Spanish public universities*

This section presents the results of the efficiency analysis. Overall, the findings in Table 4 and Figure 1 reveal that, on average, Spanish publicly funded TTOs improved their technology transfer productivity level by 4%, and that technology transfer productivity declines after 2009 to the level of 1.73% in the period 2010-2011.

----- Insert Table 4 about here -----

Additionally, Figure 2 shows the results for the components of the Malmquist TFP index. The dotted line in the figure shows the operating efficiency change, which is linked to the catching-up effect and is computed for each university as the difference in the distance to the efficiency frontier between period t and $t+1$. The technical change (continuous line in Figure 2) captures the shift in the frontier between period t and $t+1$, thus unveiling the progress or regress of the analyzed TTOs with similar input-output configurations. Results in the figure show that technology transfer productivity is mainly driven by positive shifts in the efficiency frontier (on average 2.54%), with the exception of the period 2007-2008 where the technology transfer frontier regressed by 3.58%.

Consistent with the period of economic downturn that characterized Spain's economy, Spanish public TTOs show a fall in operating efficiency after 2009, that is, their distance to the technology transfer frontier has increased (deteriorated) between period t and $t+1$ as a result of the ineffective utilization of resources in the production of technology-transfer outcomes.

----- Insert Figures 1 and 2 about here -----

A closer look at the results reveals that the number of efficient universities placed on the technology transfer frontier varies between 13 (2009) and seven (2011). Additionally, we note that seven TTOs affiliated to public universities consistently shape the technology transfer frontier, that is, they are efficient in four or five periods: Universidad of Sevilla, University of Oviedo, University of Salamanca, Polytechnic University of Catalonia, University Pompeu Fabra, Polytechnic University of Valencia, and Polytechnic University of Madrid.

These TTOs are benchmark targets for inefficient TTOs, and they show a greater average level of technology transfer outputs, compared to inefficient institutions: 4.63 spin-offs (inefficient universities: 2.14 spin-offs), 9.83 licenses (inefficient universities: 3.30 licenses), and 13.74 patents (inefficient universities: 5.71 patents). For each technology transfer output, the comparison of the average values between efficient and inefficient TTOs is statistically significant at 1% level (Kruskal-Wallis test).

Finally we note that efficient TTOs affiliated to polytechnic institutions report the highest level of technology transfer outputs (spin-offs: 7.46, licenses: 15.80, and patents: 22.80). This result is in line with prior research emphasizing the superior technology transfer orientation of TTOs working in universities with close ties to the industry, such as polytechnics and institutions with engineering schools (see e.g., Anderson et al., 2007; Caldera and Debande, 2010; Perkerman et al., 2013; Siegel et al., 2003).

5.2 Second stage analysis: Aspiration performance and technology transfer productivity

Table 5 reports the estimates of the random-effects regression models linking aspiration performance and technology transfer productivity. Model 1 is the baseline model which includes the aspiration performance levels and the control variables. Model 2 includes the main effects of aspiration performance based on both TTO-specific and market levels.

To address the threat of collinearity, we computed the average variance inflation factor (VIF) for all variables. The average VIF value for model 1 3.03 and ranges between 1.22 and 6.67, while for model 2 the average VIF is 6.75 (ranging between 1.23 and 5.88). Note that all the VIF values do not exceed 10—a generally accepted rule of thumb for assessing collinearity. The results for this diagnostic test do not raise collinearity concerns.

----- Insert Table 5 about here -----

To aid in the interpretation of the results, we plot the aspiration performance variables based on estimates from model 2 (equation (4)). The results are presented in Figure 3. The vertical axis indicates the estimated technology transfer productivity, and the horizontal axis indicates the aspiration performance levels. Control variables are set at their sample means.

----- Insert Figure 3 about here -----

Concerning the key results of the analysis, from model 1 we note that the coefficient for own aspiration performance is positive and statistically significant. This result indicates that TTOs whose technology transfer portfolio is above their own aspiration performance level show

higher levels of technology transfer productivity, that is, increased technology transfer complexity enhances productivity.

The pattern of own aspiration performance in model 2 of Table 5 suggests that technology transfer productivity increases for TTOs that increase the complexity of their technology transfer portfolio. One possible explanation for this result is that TTOs benchmark their own aspiration level to introduce changes in their technology transfer portfolio, irrespective of whether the TTO's portfolio is below or above their own aspiration level. This result is in line with the competitive advantage view of organizational change that underlines the role of change based on own aspiration levels to consolidate market positioning (Iyer and Miller, 2008). This indicates that TTOs benchmark the outcomes of their own portfolio, and that increased diversification in the TTOs' portfolio with respect to their own aspiration level yields superior productivity results.

In contrast, TTO actively engaging in technology transfer activities above market aspiration show a significant deterioration in their technology transfer productivity (model 2 in Table 5). Following the decomposition of the Malmquist index presented in equation (2), this result may well originate from variations in operating efficiency (*TE*) or from shifts in the technology (*TC*). Variations in the operating efficiency component (*TE*) are linked to the exploitation of available resources as it indicates if any focal TTO is moving closer or farther away from the efficiency frontier (catch-up effect); while technical change (*TC*) measures the shift in the technology that result from decision-making processes, in terms of resource exploitation and output production (Grifell-Tatjé and Lovell, 1999). Thus, by analyzing the components of the Malmquist index we can test whether the negative effect on productivity of portfolio's complexity above market aspirations comes from an inefficient use of resources (variations in *TE*), or from factors linked to technical change (*TC*) that can be related to organizational inertia, such as the ineffective introduction of new technologies and the development of strategies or policy-driven actions associated with the greater (or lower) exploitation or specific resources.⁴

Looking at the results we note that the productivity level of TTOs whose portfolio's configuration is below market aspirations (Malmquist index: 1.09) is significantly higher than that reported for TTOs whose portfolio's complexity is above market aspirations (Malmquist index: 0.96) (Kruskal-Wallis test: 11.30, p -value < 0.001). An examination of the productivity components reveals that this gap is caused by significant differences in operating efficiency (*TE*) (Kruskal-Wallis test: 4.75, p -value = 0.028): TTOs whose portfolio's complexity is below

⁴ Literature on the definition and causes of technical change is extensive. In this study, technical change refers to shifts of the production function in the input-output space that originate from different combinations in the input-mix and the output-mix. In the context of non-parametric productivity models, a more in-depth analysis of technical change can be found in Kumar and Russell (2002) and Grifell-Tatjé and Lovell (2015).

market aspirations = 1.05, TTOs whose portfolio's complexity is above market aspirations = 0.95. The comparison of the technical change (*TC*) component between the two groups yields a not significant result (Kruskal-Wallis test: 2.33, *p*-value = 0.127).

Instead of organizational inertia (Iyer and Miller, 2008), these findings indicate that greater diversification of TTOs' portfolio may increase the complexity of the operational tasks necessary to generate technology transfer outcomes, which causes the reported falls in the productivity level of TTOs whose portfolio reports a complexity level above market aspirations.

6. Discussion, implications and concluding remarks

In this study, we propose that TTOs' technology transfer productivity is a function of scientists' human capital and TTO's available resources. Furthermore, we argue that the role of TTOs as driving force of change, along with differences in the configuration of the TTO's technology transfer portfolio, have implications for the technology transfer productivity of TTOs affiliated to public universities. Our approach offers a compelling vision of how TTOs seek to enhance their productivity levels through strategic actions linked to changes in the configuration of their technology transfer portfolio.

Overall, results suggest that technology transfer productivity of Spanish public TTOs improved, on average, 4% between 2006 and 2011 and that, coinciding with the economic slowdown in Spain, technology transfer productivity declined between 2009 and 2011.

At the organizational level, change is difficult but necessary. Nevertheless, organizational change entails inherent risks (Labianca et al., 2009). Therefore, the analysis of the processes underlying organizational change is critical to understand the trade-offs between resource allocation policies and the subsequent change in organizational routines and processes. Our result that changes in the TTOs' portfolio based on the portfolio configuration of other TTOs may cause unintended negative effects on productivity confirms this argument. We argue that this result might reflect that changes in the TTOs' technology transfer portfolio modify operational tasks and the way the TTOs exploit their resources.

Prior work often assumes that organizations benchmark their market peers to form their performance aspiration levels, thus ignoring the possibility that organizations mirror to themselves when it comes to create their performance aspirations (Chen and Miller, 2007). We show that, among TTOs, enhanced productivity follows organizational change based on the TTOs' own historical performance. The findings are in line with studies emphasizing that superior performance is not exclusively linked to the use of market peers or industry average values as reference point (Baum and Dahlin, 2007; Labianca et al., 2009). This result indicates that, in their search for non-local information, TTO decision-makers might be constrained by focusing on a limited number of potentially similar TTOs and strategic factors. By benchmarking heterogeneous TTOs—in terms of both available resources and the configuration

of their technology-transfer portfolio—managers may adopt strategic actions that are not compatible with the configuration of their resources, which translate into ineffective changes in the TTOs' technology-transfer operations and, consequently, poor productivity results.

On contrary, the positive effects on TFP of changes in the TTOs' portfolio based on internal information may well reflect an effective resource exploitation policy. TTOs have strong incentives to modify the configuration of their technology-transfer portfolio, irrespective of whether their performance is above or below their own aspiration level. By benchmarking their own historical record, TTOs generate changes more aligned with the configuration of their input-output set, thus incurring in lower adaptation costs. For example, internal actions that may strengthen the TTO's productivity include the support of team work dynamics among employees, as well as the introduction of both training programs and continuous improvement processes that emphasize learning. These actions may constitute a source of competitive advantage (Baum and Dahlin, 2007). Also, the exploitation of these factors signals the extent to which TTOs strive for superior performance apart from external comparisons.

The findings of this study have relevant policy implications. Our results suggest that the maximization of all types of technology transfer outputs should not necessarily be the objective of TTOs affiliated to public universities. By definition, TTOs are catalysts of change and innovation, and the successful commercialization of inventions requires specific investments, in the case of TTOs the creation of efficient organizational structures and the recruiting of highly skilled staff who support the transfer of new knowledge to the industry.

We suggest that policy makers and TTO managers need to turn their attention to the characteristics of the TTO's operational processes when considering the introduction of strategic changes that will modify the TTO's technology transfer portfolio. Drastic changes in the configuration of the technology-transfer portfolio as a result of the benchmarking of own and market aspiration levels have different effects on technology transfer productivity. The analysis of the productivity patterns of TTOs reveals that benchmark own performance might promote the engagement in efficient changes of TTOs' technology transfer portfolio, thus leading to superior TFP levels. On contrary, benchmarking market peers—other TTOs—might prove itself ineffective to enhance technology transfer productivity. The prioritization of changes in the technology-transfer portfolio based on the market aspiration levels might increase operational costs that are detrimental to both learning and productivity (Chen and Miller, 2007; Iyer and Miller, 2008).

It must, however, be mentioned a series of limitations to the present study that, in turn, represent avenues for future research. First, like other studies on productivity (see, e.g., Agasisti and Wolszczak-Derlacz, 2015; Berbegal-Mirabent et al. 2013), the data do not permit the direct analysis of the underlying productivity process. We present various interpretations of how technology transfer productivity is conditioned by TTOs' practices; however, we do not

evaluate how productivity varies at different stages of the knowledge generation process, nor do we assess the procedures through which scientists generate—individually or collectively—new knowledge and channel it to the TTO. Further research on this issue would be valuable. For example, future studies should evaluate the researchers' response to incentives created by TTOs, and determine in detail both the conditions under which academics engage in technology transfer activities and how the TTOs' operations affect these processes. Second, cultural contexts, different regulatory frameworks, and variations in the flexibility and development of technology transfer activities affect the impact of TTOs' policies on technology transfer productivity. The geographic specificity of the study calls for obvious caution when interpreting and generalizing its findings.

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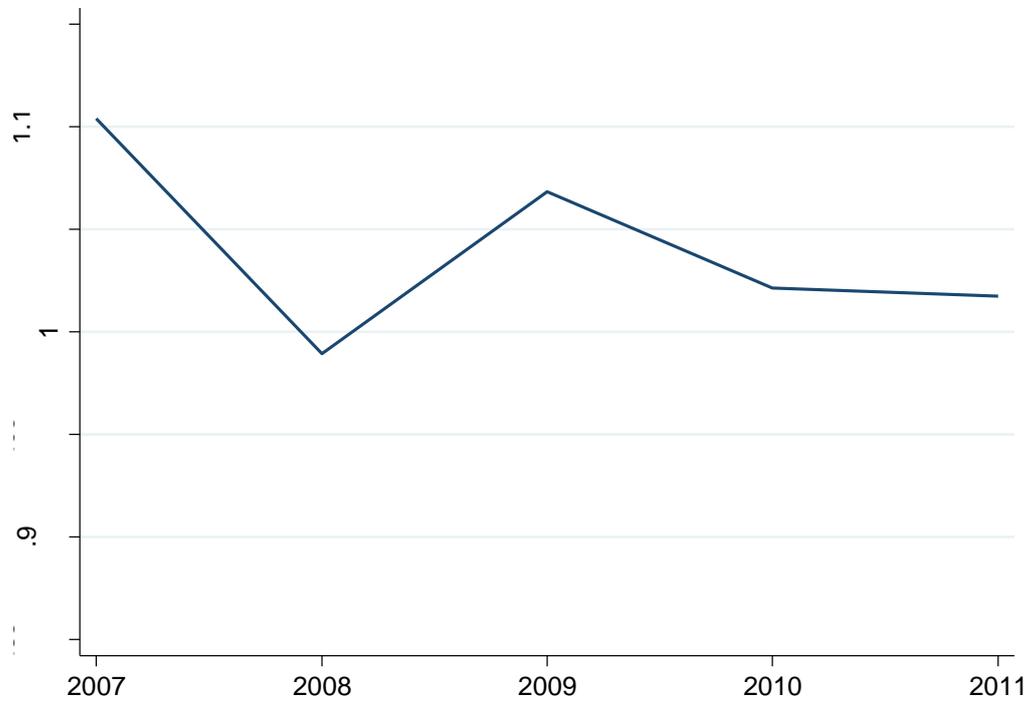
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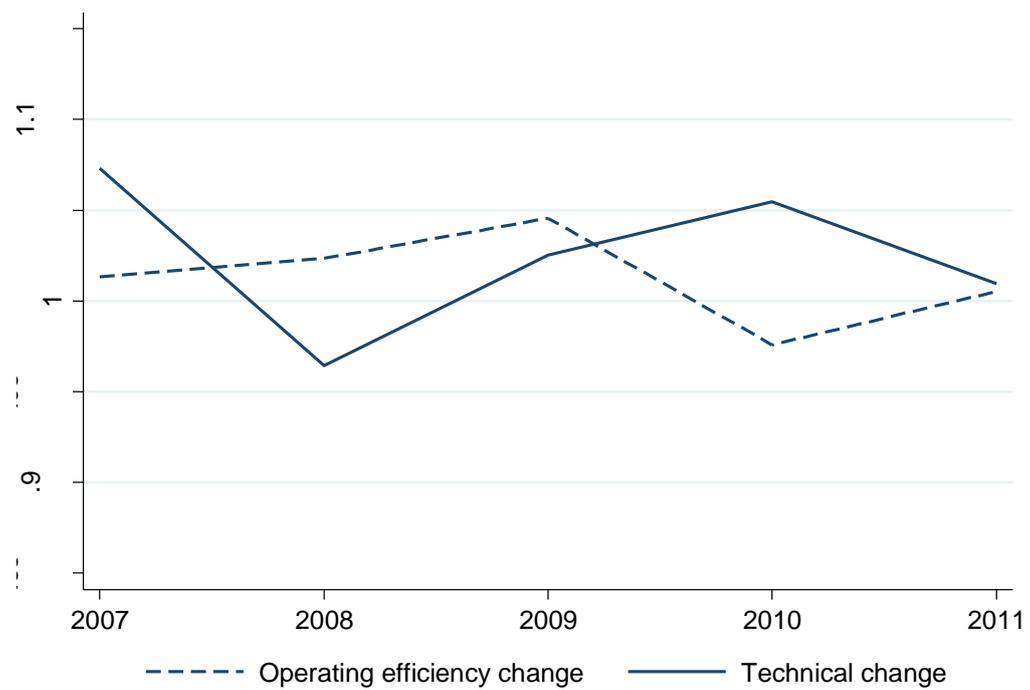
List of Figures

Figure 1. Productivity results: Malmquist TFP index



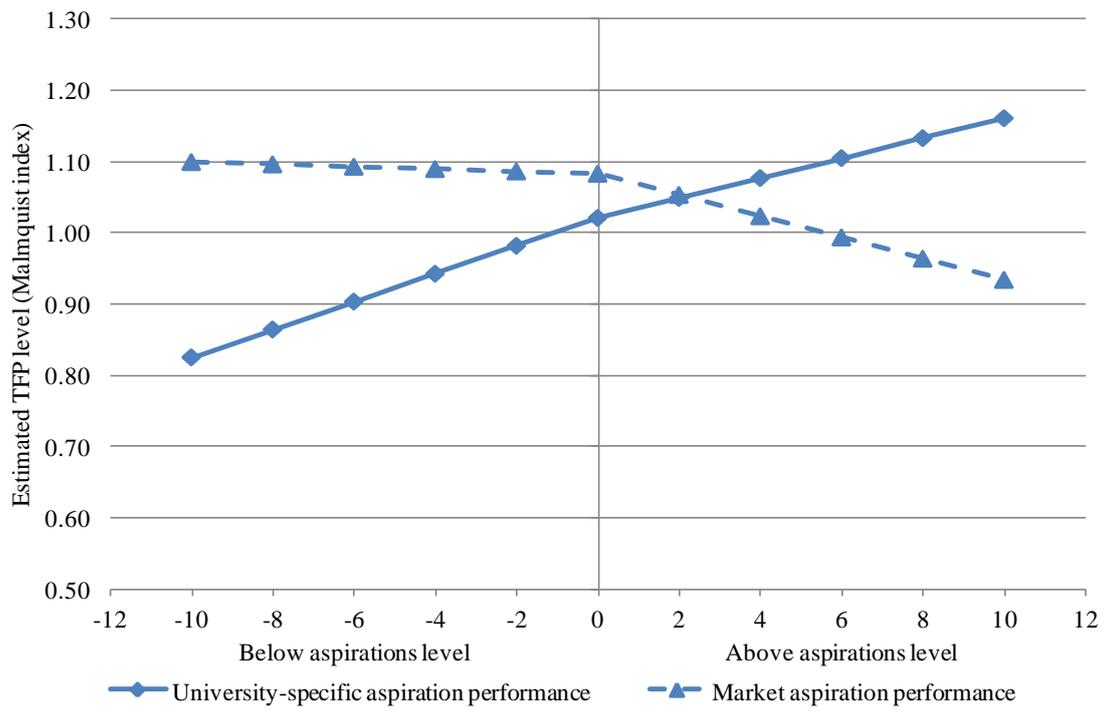
Source: Authors' elaboration.

Figure 2. Operating efficiency and technical change



Source: Authors' elaboration.

Figure 3. The relationship between aspiration performance and total factor productivity



Source: Authors' elaboration

List of Tables

Table 1. Technology transfer efficiency of Spanish public TTOs: Descriptive statistics for the input-output set

	Mean	Std. dev.	Minimum	Maximum
Inputs				
(x1) Faculty	2132.54	1299.38	446	7539
(x2) TTO technology-transfer staff	2.61	1.81	1	11
(x3) TTO administrative staff	12.49	12.61	1	92
Outputs				
(y1) Spinoffs	2.68	3.57	0	22
(y2) Patents	6.53	7.46	0	47
(y3) Licenses	4.34	7.10	0	72

Number of observations: 264 (44 observations during 2006-2011).

Table 2. Technology transfer efficiency of Spanish public TTOs: Descriptive statistics for the input-output set between 2006 and 2011

	x1: Faculty	x2: TTO technology- transfer staff	x3: TTO administrative staff	y1: Spinoffs	y2: Patents	y3: Licenses
2006	1988.26	2.10	12.44	3.41	4.27	4.32
2007	2031.20	2.35	12.30	2.70	4.82	4.23
2008	2078.07	2.59	12.82	2.36	4.80	3.84
2009	2124.93	2.61	13.08	2.61	6.02	3.98
2010	2249.91	2.82	11.72	2.73	9.50	4.64
2011	2322.89	3.18	12.55	2.27	9.80	5.02
Total	2132.54	2.61	12.49	2.68	6.53	4.34

Number of observations: 264 (44 observations during 2006-2011).

Table 3. Descriptive statistics for the selected variables (2006-2011)

	Mean	Std. dev.	Minimum	Maximum
Configuration of the technology transfer portfolio	32.35	6.17	11.91	41.46
TTO-specific aspiration performance (AP^{TTO})	2.45	5.47	-17.56	14.95
Market aspiration performance (AP^{MKT})	0.82	5.08	-16.55	7.15
University size (faculty)	2,161.40	1,314.47	446	7,539
University age (years)	141.34	224.33	10	793
TTO size (total staff)	15.09	13.46	3	94
TTO age (years)	18.00	4.00	5	28
Science park	0.66	0.47	0	1
Polytechnic university	0.07	0.25	0	1

Number of observations: 264 (44 observations during 2006-2011).

Table 4. Malmquist TFP index: Results

	Malmquist index (TFP) ($M(x_t, y_t, x_{t+1}, y_{t+1})$)	Technical change (ΔTE)	Technological change (ΔTC)
2007	1.1040	1.0134	1.0733
2008	0.9892	1.0234	0.9642
2009	1.0684	1.0456	1.0254
2010	1.0213	0.9758	1.0546
2011	1.0173	1.0052	1.0095
Total	1.0400	1.0127	1.0254

Number of observations: 220 (44 observations during 2007-2011).

Table 5. Regression results: The relationship between aspiration performance and technology transfer productivity

	Model 1	Model 2
TTO-specific aspiration performance (AP^{TTO})	0.0154 (0.0049)***	
Market aspiration performance (AP^{MKT})	-0.0050 (0.0055)	
TTO-specific aspiration performance ($AP^{TTO} < 0$)		0.0140 (0.0065)**
TTO-specific aspiration performance ($AP^{TTO} > 0$)		0.0196 (0.0084)**
Market aspiration performance ($AP^{MKT} < 0$)		-0.0149 (0.0116)
Market aspiration performance ($AP^{MKT} > 0$)		-0.0164 (0.0076)**
University size (ln faculty)	-0.0599 (0.0364)*	-0.0606 (0.0357)*
University age (ln years)	-0.0134 (0.0142)	-0.0150 (0.0144)
TTO size (ln total staff)	0.0316 (0.0340)	0.0375 (0.0361)
TTO age (ln years)	0.0364 (0.1372)	0.0370 (0.1395)
Science park	0.0139 (0.0416)	0.0163 (0.0421)
Polytechnic university	0.0197 (0.0407)	0.0241 (0.0514)
Time dummies	Yes	Yes
Intercept	1.3688 (0.3406)***	1.3697 (0.3440)***
Wald test (chi2)	42.40***	48.36***
R2 (overall)	0.1382	0.1434
Hausman specification test	7.70 ($p = 0.56$)	6.75 ($p = 0.82$)
Average VIF (minimum – maximum)	1.93 (1.22–2.61)	2.81 (1.25–5.94)
Observations	220	220

Robust standard errors are presented in brackets. *, **, *** indicate significance at the 10%, 5% and 1%, respectively.