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The efficiency of universities' knowledge transfer activities: A multi-output approach beyond patenting and licensing

by

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Abstract

Using data from the United Kingdom, we analyse the relative efficiency with which university institutions use their financial and human resources to produce a broad range of knowledge transfer outputs, including intellectual property disclosures, research and consultancy contracts, professional training courses, and public events. The efficiency of this multi-input, multi-output transformation process is computed using data envelopment analysis; bias-corrected efficiency scores and bootstrapped standard errors are used in order to deal with the statistical problems arising in connection with performing inference on non-independent efficiency scores. By including a broader range of knowledge transfer outputs in the computation of efficiency, we find that some universities that do not focus mainly on the filing and commercialization of intellectual property, can nonetheless efficiently engage in knowledge transfer. Efficiency is linked to specialization in a few subject areas, as well as to greater orientation towards the social sciences and business. Universities operating either at a very small or at a very large scale are more likely to be efficient, with a negative effect of scale, in general, on the probability to be efficient. Research and teaching intensity have no significant impact on efficiency in knowledge transfer.

Key words: university performance, knowledge transfer, data envelopment analysis, efficiency, returns to scale, HE-BCI survey

JEL codes: O32 - Management of Technological Innovation and R&D; D24 - Production; Cost; Capital; Capital, Total Factor, and Multifactor Productivity; Capacity; C34 - Truncated and Censored Models; Switching Regression Models

1. Introduction

As knowledge transfer activities have gained increasing prominence within universities, researching what institutional factors underpin their efficient performance can provide university institutions with useful empirical evidence in order to better organize their knowledge transfer processes. This understanding is also relevant from a policy viewpoint. Increasingly, policies have been implemented that encourage universities to engage in knowledge transfer and sometimes reward them for their successful knowledge transfer performance. For example, in the United Kingdom several grants in support of knowledge exchange - the Higher Education Innovation Fund in England, the Innovation and Engagement Fund in Wales, the Knowledge Transfer grant in Scotland and the Higher Education Innovation Fund in Northern Ireland – are allocated to universities on the basis of the income they accrue from knowledge transfer activities (HEFCE, 2011). In Australia, universities' knowledge transfer performance measurement is based on the commercial returns from the selling or licensing of IP (PhillipsKPA, 2006).

However, such policies are often based on fragmented empirical evidence, as academic investigations into what drives the efficient performance of universities' knowledge transfer activities have emerged only recently (Curi et al., 2012). Moreover, the literature often adopts a rather narrow approach to which activities constitute "knowledge transfer". In fact most studies focus on the commercialization of research results embedded in intellectual property protection instruments such as patents and software licenses, or the transformation of university research findings into intellectual property. Instead, it is increasingly acknowledged that the channels through which universities transfer knowledge to their stakeholders in the broader economy and society are numerous (Bekkers and Bodas Freitas, 2008; Boardman and Ponomariov, 2009), and indeed patenting and licensing activities only provide a small part of the picture, particularly relevant to a subset of science-based academic disciplines in fields such as chemistry, pharmacy, biotechnology, information technology and engineering (Harabi 1995; Brouwer & Kleinknecht 1999; Litan et al., 2008).

This study examines the efficiency of universities in performing a broader range of knowledge transfer activities beyond the patenting and licensing activities that have been the focus of most research carried out so far. Using data from the United

Kingdom, it explores whether institutions' relative efficiency changes when adopting a broader approach to knowledge transfer. It also investigates whether the efficiency of universities' knowledge transfer processes is related to characteristics of the university institutions and of the environment in which they operate. Understanding how efficiency in knowledge transfer is affected by institutional variables such as size of knowledge transfer operations, specializations in terms of subjects offered, research and teaching intensity, is important in order to support evidence-based policymaking in an area that is receiving increasing attention from the government and the public.

The paper is structured as follows. In the next section, we briefly review the literature on the efficiency of universities' technology transfer activities. In section 3, we present a brief description of the methodologies used to investigate the efficiency of production units, and we describe the data and the empirical strategy that we adopt in this paper. In section 4, we present our empirical results and in section 5 we draw some conclusions and implications for policy.

2. The efficiency of universities' knowledge transfer activities: expanding the framework

Since the early 2000s a growing number of studies have investigated the efficiency with which universities engage in knowledge transfer (for a recent review see Siegel, 2007). These studies are usually based on a production function framework, where a frontier of efficient combinations of inputs and outputs is constructed empirically and an institution's technical inefficiency (inability to produce the maximum amount of output given one's inputs, or inability to minimize the use of inputs given one's output) is measured in terms of distance from the frontier. Such frontier can be estimated parametrically using stochastic frontier estimation (Aigner et al., 1977; Meeusen and Van den Broeck, 1977) or non-parametrically using data envelopment analysis (Charnes et al., 1978).

Table 1 summarises approaches adopted by some recent studies that investigate the efficiency of universities' knowledge transfer operations, relying upon several methods: stochastic frontier estimation (SFE), data envelopment analysis (DEA), or regression analysis on direct measures of performance. The knowledge transfer transformation process that is modelled is either the commercialization of research results embedded in intellectual property protection instruments like patents and software licenses (Siegel et al. 2003; Chapple et al., 2005), or the transformation of university research findings into intellectual property (Curi et al., 2012) and other outputs (Thursby and Kemp, 2002; Anderson, Daim and Lavoie, 2007; Berbegal-Mirabent, Lafuente and Solé, 2013). The range of outputs of universities' knowledge transfer processes is generally narrow, mainly measured in terms of invention disclosures, patents applied for and granted, and licenses issued, with a few studies also including research agreements (Kemp and Thursby, 2002) and spinoff companies (Anderson, Daim and Lavoie, 2007; Rogers et al., 2000; Caldera and Debande, 2012; Berbegal-Mirabent, Lafuente and Solé, 2013).

Both Chapple et al. (2005) and Curi et al. (2012) find that TTOs exhibit low-levels of absolute efficiency, and large inter-organizational variations. In terms of the determinants of a university's performance and efficiency in technology transfer, common findings from this stream of literature emphasize the role of the characteristics of the university institution, such as subject specialization (having a large, high quality faculty in biological sciences and engineering is significantly related to efficiency in commercializing licenses, while the size and quality of physical science faculty is insignificant; Thursby and Kemp, 2002), ownership (in the US, private universities are more efficient; Thursby and Kemp, 2002) faculty quality, presence of a medical school or university hospital and, very importantly, the policies implemented, including the system of incentives for academic and technology transfer staff: well-defined university rules (for example, the regulation of potential conflicts of interest and the allocation of a larger proportion of royalties to the inventor) improve performance by giving researchers incentives to participate in the transfer of technology (Calder and Debande, 2012; this is in line with other studies, such as Link and Siegel, 2005; Friedman and Silberman, 2003; Debackere and Veugelers, 2005; Belenzon and Schankerman, 2007; Lach and Schankerman, 2004). Also important are the characteristics of TTO, including size, age, management practices (Siegel et al., 2002; Debackere and Veugelers, 2005), organizational structure (Bercovitz et al., 2001) as well as the economic characteristics of the region where the institution is located.

Table 1. Studies on the efficiency of universities' knowledge transfer operations

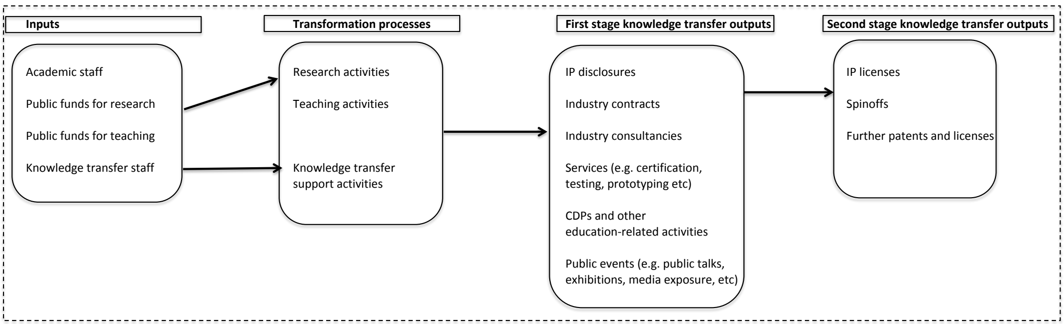
Study	Focus	Method	Inputs	Outputs
Siegel et al (2003)	113 US universities (1991–1996)	SFE	Number of invention disclosures, number of TTO employees, legal expenditures	Number of licences or licensing income
Chapple et al (2005)	50 UK universities (2002)	SFE and DEA	Number of invention disclosures, total research income, number of TTO staff, external legal IP expenditure	Number of licences or licensing income
Thursby and Kemp (2002)	112 US universities (1991-1996)	DEA	Number of TTO staff, amount of government funds received, number and quality of faculty in several subjects	Sponsored research agreements between universities and industry, number of licenses to private sector firms, royalty payments received, number of invention disclosures, university patent applications
Anderson, Daim and Lavoie (2007)	54 US universities (2001-2004)	DEA	Total research spending	Licensing income, licenses and options executed, startup companies, patents filed, patents issued
Curi, Daraio and Llerena (2012)	51 French universities (2003-2007)	DEA	Number of full time equivalent TTO employees, number of publications of the university	Patent applications, software applications
Berbegal-Mirabent, Lafuente and Solé (2013)	44 Spanish universities (2006-2009)	DEA	Total faculty, administrative staff, administrative expenses, R&D income	Graduates, number of papers published, number of spin offs created
Rogers et al (2000)	131 US universities (1996)	Regression on various performance measures		Number of invention disclosures received, number of U.S. patents filed, the number of licenses, number of start-up companies, gross licensing income
Caldera and Debande (2012)	52 Spanish universities (2001-2005)	Regression on various performance measures		Log of R&D contracts income, number of R&D contracts, log of licensing income, number of licensing agreements and number of spin-offs

However, findings from different studies are often contradictory. Some suggest that the presence of a university hospital or medical school exerts a positive effect on efficiency (Siegel et al, 2003), while others find the opposite (Thursby and Kemp, 2002; Chapple et al., 2005; Anderson, Daim and Lavoie, 2007; Curi, Daraio and Llerena, 2012). Some studies find that the size of the TTO has a positive effect on efficiency (Rogers et al, 2000; Thursby and Kemp, 2002; Caldera and Debande, 2012; Curi, Daraio and Llerena, 2012), while others find that it has a negative effect (Chapple et al., 2005). By testing appropriate restrictions on the coefficients of a parametric production function, Siegel et al (2003) find that licensing revenue is subject to increasing returns, while licensing agreements are characterized by constant returns to scale. Instead, Chapple et al. (2005) find evidence of decreasing returns to scale. Curi Daraio and Llerena (2012) formally test whether the frontier globally exerts constant, non-increasing or variable returns to scale, rejecting the null hypothesis of global constant returns to scale for French TTOs, in favour of global variable returns to scale.

While most studies focus on a limited set of knowledge transfer activities, namely patenting and licensing, it is increasingly acknowledged that the channels through which universities transfer knowledge to their stakeholders in the broader economy and society are numerous, and indeed patenting and licensing activities only provide a small part of the picture, particularly relevant to a subset of science-based academic disciplines in fields like chemistry, pharmacy, biotechnology, information technology and engineering (Levin, 1986; Harabi, 1995). Varied types of universities, with profound differences in research orientation, subject specialization, resources and engagement with their external environment, very often have very different profiles in terms of knowledge transfer engagement (Wright et al, 2008; Hewitt-Dundas, 2012) that include providing consultancies, services like certification, prototyping and design, courses for professional development, student placements, or engaging with the community in many different ways (through public talks, exhibitions, media exposure, and so on). Consequently, measuring efficiency using only a limited range of knowledge transfer outputs may disadvantage those universities that use their generic inputs to engage in a mix of knowledge transfer activities that do not involve the production or commercialization of patentable research findings.

To compute the efficiency of universities' knowledge transfer process taking into account a broader range of outputs, so as to allow for a greater variety of forms of knowledge transfer engagement, we need to describe the knowledge transfer process in broader terms. Figure 1 captures the main elements of the process of transformation of generic university inputs into knowledge transfer outputs. It extends the current frameworks adopted in the analysis of knowledge transfer efficiency such as those presented by Thursby and Thursby (2002) and Anderson, Daim and Lavoie (2007) who restricted their attention to the production of IP disclosures (first stage outputs) and their further commercial exploitation in the form of licenses and spinoffs (second stage outputs), by explicitly including other activities that allow for the direct transfer of academic knowledge to external beneficiaries, primarily businesses.

Figure 1. A broader framework to describe the knowledge transfer process



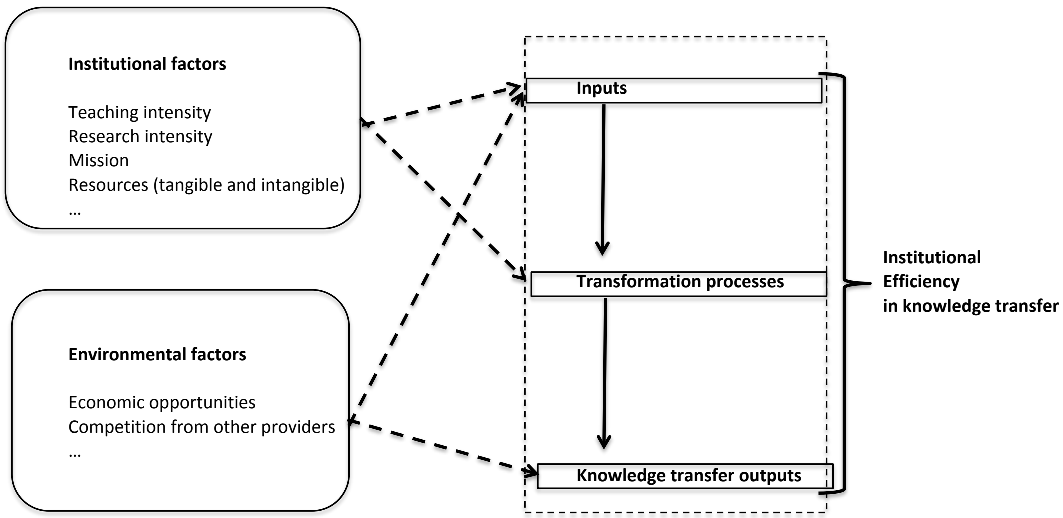
It must be noted that this framework is necessarily very simplified and only useful to explain our methodological choices in order to measure the efficiency of knowledge transfer processes; it does not aim to capture the full complexity of transformation processes occurring within universities, of which this knowledge transfer process constitutes only a part. For example, the range of inputs that enter into universities' research and teaching activities can be wider (research and teaching funds can be sourced from students, businesses and charities, and administrative staff can also play a role in these processes, not to mention the important inputs that students offer to teaching and sometimes research activities), and the range of outputs that are concurrently produced through research and teaching activities is also much broader (publications and qualified and trained human resources are the most obvious).

Using data from the United Kingdom's Higher Education Business and Community Interaction Survey (HEBCI) - a yearly survey of all universities in England, Wales, Scotland and Northern Ireland, implemented since 1999 and currently managed by the Higher Education Statistics Agency - we aim to assess whether universities' relative efficiency changes when a broad range of knowledge transfer activities beyond patenting and licensing are considered (as opposed to the more widespread approach based only on patenting and licensing), and to identify which universities benefit from the adoption of a broader perspective on knowledge transfer.

We also aim to assess what institutional and environmental factors are linked to greater efficiency, with the objective to provide useful indications for knowledge transfer policies intending to support efficient knowledge transfer performance. In fact, institutional and environmental factors constrain the university's availability of inputs that can be deployed in knowledge transfer processes, and the opportunities to generate knowledge transfer outputs.

Figure 2, expanding the knowledge transfer framework illustrated in Figure 1, summarizes the model of the relationships between knowledge transfer inputs, outputs and institutional and environmental factors underpinning our approach.

Figure 2. Relationships between inputs, outputs and institutional and environmental factors



Efficiency is measured as the relationship between input and output employment. Institutional factors affect the measurement of efficiency to the extent that they affect the availability of inputs and the manner of their deployment within the university's transformation processes. Environmental factors may affect both the availability of inputs (for example, intense competition from resources, both financial and human, may reduce their availability) and the opportunities to generate outputs (for example, knowledge transfer opportunities should be higher in more economically prosperous regions).

3. Methodology

3.1. Measuring the relative efficiency of different production units

We compare different university institutions with respect to their efficiency: their ability to produce, given their limited resources, the greatest possible amount of knowledge transfer outputs. Two main approaches can be used to measure and compare the relative efficiency of different economic units engaged in the same production process. Stochastic frontier estimation (SFE) (Aigner et al., 1977; Meeusen and Van den Broeck, 1977) is based on the estimation of a production function, where differences in performance across units are attributed to an error term, εi, which has two components ($\varepsilon i = Vi - Ui$): statistical noise Vi (a symmetric, independently and normally distributed random error component) and an inefficiency component Ui. The latter is a non-negative error term which accounts for the failure to produce the maximum output, given the set of inputs used; it is assumed to be independently and half-normally distributed (as units are either on the frontier or below it). To test the determinants of inefficiency, the inefficiency term Ui can then be regressed onto a set of independent and control variables. In more recent models (Battese and Coelli, 1995), both the production function (including the inefficiency term) and the determinants of relative inefficiency are estimated simultaneously.

While SFE, as a parametric approach, has several advantages (see for example Chapple et al, 2005, for a discussion), it also has the critical limitation that only single-output production processes can be modelled. The analysis of processes that involve the simultaneous production of different outputs require to either estimate alternative models (one for each different output, as in Chapple et al., 2005) or aggregate the different outputs using a common metrics (the different outputs can be expressed in monetary terms and aggregated, if market prices for them exist; Ray, 2004). Another crucial limitation is that SFE imposes a parametric functional form on the relationship between inputs and output which is expected to hold over the entire input range (Chapple et al., 2005).

The other approach to efficiency computation, called data envelopment analysis (DEA) (Charnes et al., 1978) consists in numerically computing an "efficiency frontier" of the best performing units, and positioning the other units in relation to this frontier. This method has been used extensively to compute relative productivity in service industries, including the education sector (Charnes et al., 1994), because it allows to calculate the efficiency of production processes that generate multiple outputs some of which may not have easily identifiable market prices. Fitting the linear frontier requires identifying, for each combination of inputs used by the observed units, the maximum output that could be produced given that input combination: the set of maximum output/input ratios constitutes the efficient frontier, and the relative efficiency of each unit can be computed by comparing the unit's actual output with the maximum output that could be produced using the same combination of inputs. In practice, this requires solving a linear program: finding the set of weights that maximize each unit's average productivity (ratio of its weighted combination of outputs to its weighted combination of inputs) subject to the constraints that all weights are non-negative and all ratios are smaller or equal to one (that is, maximum efficiency is imposed to be equal to 1).

Suppose that there are N units, each using n inputs $x_i, \ldots x_n$ to produce m outputs $y_1, \ldots y_m$. The linear program identifies the set of weights u_i $(i = 1 \ldots . n)$ and v_j $(j = 1, \ldots, m)$ such that, for each unit t:

$$\max \frac{\sum v_j \, y_t}{\sum u_i x_t}$$

s.t.

$$\frac{\sum v_j \, y_t}{\sum u_i x_t} \leq 1 \qquad (t = 1, \ldots . N)$$

$$u_i, v_j \ \geq 0 \ \forall \ i, j$$

Since there are an infinite number of solutions to this problem, a further constraint is added:

$$\sum u_i x_t = 1$$

Once the efficient frontier is computed this way, the efficiency of each unit relative to the frontier is measured using a distance function. Usually, inefficiency is presented in terms of a score $\frac{1}{\lambda} \leq 1$ (Shepherd distance) which identifies the fraction of the unit's actual output to its corresponding "optimal output" (the maximum output obtainable given the combination of inputs used by the unit): correspondingly, the reciprocal score $\lambda \geq 1$ (Farrell-Debreu distance) identifies the increase in output that the unit would need to accomplish if it was to become technically efficient.

DEA models come in different specifications. The model can have an input or output orientation, that is, efficiency can be computed in terms of maximum output that can be produced given a certain combination of inputs, or of minimum inputs that can be used to produce a given output. The model can accommodate constant or variable returns to scale, according to the restrictions imposed on the efficiency scores. Different types of efficiency frontiers can be fitted: piecewise linear (or "convex hull") as in the standard DEA approach proposed by Charnes et al. (1978), or "staircase shaped" as in the Free Disposal Hull approach (Deprins et al., 1984).

The nonparametric method has also several drawbacks. One important problem is that, since the method does not allow for statistical noise, the frontier can be strongly influenced by, for example, measurement errors and outliers: as a unit's efficiency is computed with respect to the frontier of the best performing institution, even one or two "super efficient" units shift the frontier outwards and reduce the efficiency of comparable institutions[1]. Recently, some techniques like order-*m* and order-α efficiency (Cazals, Florens and Simar, 2002; Daraio and Simar, 2005) have been proposed to introduce stochasticity in the estimation of the frontier. Another issue that is relevant for our present purposes concerns the estimation of the determinants of the efficiency of different institutions. Two-stage estimations, whereby efficiency scores are estimated in the first stage and regressed on several organizational and environmental variables in the second stage, using OLS or TOBIT models, have been widely used (an overview is presented in Simar and Wilson, 2007). It has however been pointed out that this approach is problematic as the DEA efficiency scores are serially correlated, which invalidates standard approaches regarding statistical inference. Simar and Wilson (2000) have proposed a bias correction procedure to take care of this problem, thus allowing for more precise estimates in a two-stage setting.

In the present paper, we aim to measure universities' efficiency in the performance of a range of knowledge transfer activities that goes beyond patenting and licensing. Because such activities produce a variety of outputs that are difficult to commensurate (as it is often not possible to find market prices for them), we focus on non-parametric frontier estimation, using data envelopment analysis. To perform inference on the efficiency measures such derived, we rely upon the bias correction procedure suggested by Simar and Wilson (2000).

3.2. Data and empirical strategy

We use data about universities in the United Kingdom, drawn from two main data sources, both currently managed by the UK's Higher Education Statistics Agency (HESA). One is the database Heidi, which collects numerous data about university institutions' financial, human and capital resources, as well as their teaching and research activities. The other is the Higher Education Business and Community Interaction (HEBCI) survey, which collects information about universities' knowledge transfer infrastructures, strategies and engagement. The survey includes a broad range of activities spanning collaborative research and regeneration programmes, contract research, consultancies, intellectual property protection and licensing, spin off activities, courses for professional development, equipment and facilities-related services, and various forms of community engagement (such as public lectures and other events). Currently, it is the broadest systematic survey of universities' knowledge transfer activities (Rossi and Rosli, 2013), and as such it measures a wide variety of knowledge transfer outputs.

The choice of inputs and outputs for this kind of exercise depends on the type of production process we are interested in. In this study, we focus not only on the process of transformation of research results into intellectual property, or of intellectual property into commercialized licenses and licensing income, but on the broader transformation process through which university institutions employ their financial and human resources to produce knowledge, and in turn transfer it to external stakeholders. This process can involve knowledge produced in the social sciences and the humanities, as well as in the natural, technical and medical sciences.

In line with this approach, we use as inputs a number of general resources that universities use in the production and transfer of knowledge (amount of research and teaching grants from funding councils[2]; number of staff employed in knowledge transfer functions, number of academic staff in the natural sciences and medicine, in technical and engineering subjects, in the social sciences and business and in the arts and humanities)[3], and a broad range of activities as outputs (number of intellectual property disclosures, number of research and consultancy contracts, number of days of courses for professional development (CDP) delivered, number of academic days employed to deliver public events).

As we want to focus on the process of transformation of the university's generic resources into outputs that are suitable to be transferred to the economic system, rather than on the specific process of commercialization and dissemination of such outputs, we do not include outputs that emerge from a process of further exploitation of the outputs already considered, such as IP licenses and spinoffs emerging from university disclosures, joint university-industry patents and publications emerging from research contracts, and so on (what has been termed "second stage knowledge transfer outputs" in Figure 1). Moreover, we do not consider all of the possible outputs that can emerge from knowledge transfer activities, due to data limitations. Information about facilities and equipment-related services is collected in the HEBCI survey, but it is not possible to distinguish between knowledge-based services (such as prototyping, certification and quality assessment) and services that just exploit the university's infrastructure like the rental of equipment and rooms, so we leave these activities out too. Other activities (such as the number of student placements, various types of engagement with the local community, with the public sector and with policymakers) are not measured in the survey (Rossi and Rosli, 2013). Furthermore, we have chosen to focus on activities through which the university attempts to

[2] It has been pointed out that the DEA technique is formulated on the quantity space of outputs and inputs (Färe et al., 2012), while research funds are not directly defined in physical terms. However the choice to include measures of funding is well established in the line of research on the efficiency of knowledge transfer activities (Thursby and Kemp, 2002; Siegel et al., 2003; Chapple et al., 2005; Anderson et al., 2007; Berbagal-Mirabent et al., 2012). It could be argued that although research funds are not directly mappable onto physical space, they are usually constrained to be spent onto the purchase of physical inputs (hours of research labour, scientific equipment) and as such they provide a proxy for the inputs acquired.

[3] A similar set of inputs has been adopted by Thursby and Kemp, 2002, who have also included a measure of faculty quality, by subject area. The subject areas they considered are only biology, engineering and physical sciences, in line with a "science based" view of knowledge transfer.

transfer knowledge to specific stakeholders in the economic, political and social community; we have not included therefore scientific publications and other forms of dissemination of academic results, which do not presuppose an attempt to transfer knowledge to specific users (these are in fact usually considered as outputs of research activities rather than as part of knowledge transfer activities).

Since there may be a lag between the use of inputs (i.e. research funds) and the production of outputs, we use five-year averages of the period 2006-2011 (averages over several years have also been used by Thursby and Kemp, 2002; Anderson, Daim and Lavoie, 2007; Daraio, Curi and Llerena, 2012). Our dataset includes 160 universities, however the estimates of efficiency are done on a reduced sample of 80 universities that employ strictly positive quantities of all the inputs and outputs considered in the estimations[4].

Table 2 describes the input and output variables used in order to compute the institutions' efficiency and reports their main descriptive statistics.

Table 2. Inputs and outputs used in the computation of DEA efficiency scores, and their main descriptive statistics

Variable name	Description	N	Mean	Standard Deviation	Maximum value	Minimum value

[4] The 80 universities included in the sample do not have a significantly different geographical distribution from the 80 universities that have not been included in the computation. However, they differ in respect to several institutional characteristics. When universities are categorized according to their historical origins, we find that historical universities, founded before the mid-20th century, and universities that were formerly polytechnics (institutions providing technical and vocational education that changed their status to universities in 1992) are more likely to be included while modern universities, founded after the mid-20th century, and university colleges (institutions that are only allowed to award undergraduate degrees) are more likely to be excluded. This can be explained with the fact that many modern universities and university colleges are specialized in the social sciences and humanities and do not have staff in all subjects (university colleges include art schools, conservatories and institutes of performing arts, for example) and/or do not produce all outputs (many of these universities do not patent). In fact, the universities that have been included have a significantly higher average share of academic staff in the natural sciences, medicine and engineering and technical subjects, and a significantly lower average share of academic staff in the arts and humanities, suggesting that institutions that are strongly specialized in the humanities have been excluded.

Inputs:						
FCGRANTS	Public (non industry) funding for research and teaching: total grants from funding councils received by the institution (£000)	80	80716.9	48436.2	249417.4	18409.7
KTSTAFF	Number (headcount) of staff specifically employed in a knowledge transfer capacity	80	57.3	42.9	207.6	8.8
SCIMEDSTAFF	Number (full time equivalent, FTE) of academic staff in the natural sciences and medicine	80	855.5	1042.6	4518.8	0.2
ENGTECHSTAFF	Number (FTE) of academic staff in technical and engineering subjects	80	286.0	236.2	1047.8	9.4
SOCBUSSTAFF	Number (FTE) of academic staff in the arts and humanities	80	316.6	174.4	991.4	35.4
ARTHUMSTAFF	Number (FTE) of academic staff in the social sciences and business	80	329.1	238.7	1468.0	11.4
Outputs:						
IPDISCL	Number of IP disclosures and patent applications filed	80	40.0	59.4	315.6	0.2
RESCONSULT	Number of research and consultancy contracts (excluding any already returned in collaborative research involving public funding & Research Councils)	80	957.7	2056.4	15944.8	29.0
CPD	Learner days of CPDs delivered	80	35772.8	44456.6	303030.0	46.8
EVENTS	Number of academic days employed to deliver public events	80	879.9	1731.1	11126.0	6.6

Many of the inputs used for knowledge transfer activities are used, at the same time, for research and teaching – for example, the time of academic staff and the resources provided by government funding. Therefore, it is not possible to precisely identify how much of these inputs actually goes in the production of knowledge transfer outputs; as Thursby and Kemp (2002) note, we would not be able to say whether a university that has a higher research commercialization output (for example, number of patent applications) than another, vis-à-vis a given amount of inputs, is more efficient than the latter or is simply allocating more of its inputs to activities that are more likely to produce commercializable outputs. However, our broad definition of knowledge transfer should dampen this problem to some extent; since we consider a range of knowledge transfer activities that draw upon a wide variety of university resources, we suppose that universities could allocate their inputs differently across teaching and research, or the social and natural sciences, and still enjoy similar opportunities for knowledge transfer. If that is the case, we should observe that some universities that allocate more inputs to activities that do not fit well in the standard "science based" technology transfer model, may increase their relative efficiency when outputs are measured in terms of a broad range of activities rather than just in terms of patents and disclosures.

Our empirical strategy is the following. First, we investigate whether adopting a broader approach to the knowledge transfer transformation process (considered as a multi-output process that includes other activities beyond patenting and licensing) produces appreciably different results from the adoption of a narrower approach according to which knowledge transfer only refers to the creation of new intellectual property that can be commercialized. To do so, we compute the efficiency scores of universities under two different model specifications (a narrow model which includes six inputs – *FCGRANTS, KTSTAFF, SCIMEDSTAFF, ENGTECHSTAFF, SOCBUSSTAFF, ARTHUMSTAFF* – and only one output – *IPDISCL*, and a broad model which includes the same six inputs and four outputs - *IPDISCL, RESCONSULT, CPD* and *EVENTS*). The efficiency scores, in both models, are computed using the output-oriented[5] data envelopment analysis linear programme with variable returns to scale[6] implemented in the R package FEAR (Wilson, 2008). We then check whether the universities' ranking in terms of efficiency differ in the two models, and what are the different characteristics of the universities that improve their relative rank position when moving from the narrow to the broad model of knowledge transfer.

[5] We use the output-oriented approach because universities are more interested in maximizing knowledge transfer outputs than in minimizing the inputs used in the knowledge transfer production process: in fact, most inputs are concomitantly deployed in the production of research and teaching, so, for the purpose of knowledge transfer, they can be considered as exogenously determined and (almost) fixed in the short term.

[6] The null hypothesis of constant returns to scale versus the alternative hypothesis of variable returns to scale was tested using the F-statistic test proposed by Banker (1996). The null hypothesis was rejected at 1% significance level, for both the narrow and the broad models. Using the bootstrap test of returns to scale proposed by Simar and Wilson (2002) also led us to reject the null of CRS at 1% significance, for both models. Both tests were implemented in R.

Second, just focusing on the broad (multi-output) model[7], we analyse the characteristics of efficient and inefficient universities, and we explore the institutional determinants of efficiency. We measure inefficiency using an indicator variable that takes on value 1 if the university is inefficient and zero otherwise (as in Thursby and Kemp, 2002). We compare the characteristics of efficient and inefficient universities, and examine the relationship between inefficiency and the variables denoting inputs and outputs. We then compute the impact on efficiency of a varied range of institutional and environmental factors, including: the overall scale of knowledge transfer operations of the university (proxied by the university's overall knowledge transfer income); several characteristics of the university (age of the institution, whether the university is a former polytechnic or a historical university, number of students per academic staff, research intensity, subject diversity of academic staff) and of its TTO (age of the TTO, share of knowledge transfer staff to academic staff, diversity of sources of knowledge transfer income) and of the region where it is located (regional gross value added per capita). The regressors refer to 2006/07 because we aim to test the effect of institutional and environmental variables, which affect the universities's inputs and outputs, on the efficiency measured with respect to the subsequent five years. As a robustness check, we also perform the same regression using as a dependent variable, instead of the indicator variable, the actual efficiency scores obtained (we use the bias-corrected efficiency scores, and the relative bootstrapped confidence intervals and standard errors, proposed by Simar and Wilson, 2007[8]).

4. Empirical results

[7] The narrower model, being of a lower dimensionality, is likely to have greater level of statistical precision as well as greater discriminatory power among DEA estimates. It is for this reason that, for example, Curi, Daraio and Llerena (2012), in their analysis of the efficiency of French universites' TTOs, prefer to estimate a narrower model. However, it is the main purpose of this paper to explore the efficiency implications of adopting a broader approach to knowledge transfer, beyond patenting and licensing. This requires us to explore the multi-output model in greater detail.

[8] These were obtained by implementing Algorithm 2 proposed by Simar and Wilson (2007) in R, with the support of the FEAR package (Wilson, 2008).

4.1. Comparisons of rank positions of universities under the narrow and broad models of knowledge transfer

When comparing the rank positions of universities in terms of efficiency[9], under the narrow (only one output) and the broad (four different outputs) models of knowledge transfer, we find that 30 universities (37.5%) improve their rank position in the broad model, while 50 universities (62.5%) do not improve their rank position (their rank either remains the same or worsens).

As shown in Table 3, universities that improve their position have on average a higher share of staff in the social sciences and business and a lower share of staff in medicine and the natural sciences, than those that do not improve their position. This confirms our initial conjecture that some universities that allocate more inputs to activities that do not fit well in the standard "science based" technology transfer model, may do better when outputs are measured in terms of a broad range of activities rather than just in terms of patents and disclosures. As the patent-based model best fits a narrow range of fields in the natural and applied sciences, particularly chemistry, pharmacy, biotechnology and engineering and technology, it is not surprising to find that it is universities with a greater share of staff in the social sciences and business that improve their position when a broader definition of knowledge transfer is considered.

We also find that former polytechnics are more likely to improve their position, while all other types of universities are less likely to do so. Former polytechnics have on average a greater share of staff in the social sciences and business and in the arts and humanities than historical universities, and evidence suggests that they engage in a broad range of knowledge transfer activities (D'Este and Patel, 2007) whose efficiency is better reflected when a broader approach to outputs is used.

Finally, considering the differences across mean amounts of inputs and outputs in the two groups, the universities that have improved their position have delivered significantly more days of CPDs and public events, while generating no less intellectual property disclosures and research contracts and consultancies and while using no more inputs than the others. This confirms that their improved efficiency is due to their ability to produce a varied portfolio of activities that is not taken into account when considering only a narrow model of knowledge transfer.

[9] We cannot directly compare the universities' efficiency scores under the two models, as their magnitude is only meaningful in a relative sense.

Table 3. Characteristics of institutions that have improved or not improved their rank position when moving from a narrow to a broad model of knowledge transfer

Mean share of academic staff	Not improved (50 universities)	Improved (30 universities)	t-test	p-value
Medicine and natural sciences	42.0	35.0	1.836	0.070
Technical subjects /engineering	17.0	17.0	-0.140	0.888
Social sciences and business	21.0	25.0	-1.941	0.056
Arts and humanities	20.0	23.0	-0.888	0.377
Type of instititution	% Not improved (50 universities)	% Improved (30 universities)	Chi2(1)	p-value
Historical	38.0	23.3	9.273	0.010
Former polytechnic	26.0	60.0		
Modern	36.0	16.7		
Mean amounts of inputs and outputs	Not improved (50 universities)	Improved (30 universities)	t-test	p-value
FCGRANTS	79360.2	82978.2	-0.316	0.732
KTSTAFF	55.3	60.8	-0.559	0.578
SCIMEDSTAFF	947.1	702.8	1.060	0.292
ENGTECHSTAFF	274.9	304.4	-0.522	0.603
SOCBUSSTAFF	292.8	356.3	-1.553	0.126
ARTHUMSTAFF	314.6	353.2	-0.743	0.460
IPDISCL	45.3	31.3	1.019	0.311
RESCONSULT	942.5	983.0	-0.090	0.928
CPD	22416.5	58033.4	-3.042	0.005
EVENTS	532.1	1459.6	-1.910	0.065

4.2. Inputs, outputs and their relationship with efficiency

In the rest of our analysis, we focus on the broader (four-output) model of knowledge transfer, and we explore the institutional and external determinants of efficiency.

We build an indicator variable *INEFFICIENT* that takes on value 1 if the university is inefficient (its efficiency score is less than one) and value 0 if it is efficient (its efficiency score is equal to one)[10]. We have 32 efficient universities (40%) and 48 inefficient ones (60%). On average, inefficient institutions use more inputs and produce less outputs than efficient ones. To explore the relationship between inputs, outputs and efficiency we regress the entire set of inputs and outputs combined the

[10] The reason why we construct this variable to represent inefficiency, rather than efficiency, is for consistency with our later analysis of efficiency scores, whose bias-correction procedure has been developed using the Farrel-Debreu distance measure (Simar and Wilson, 2007).

indicator variable *INEFFICIENT*. The correlation matrix between input and output variables is reported in Appendix A. From the logit regression shown in Table 4 (column (1)) we can see that inputs have, as expected, a positive effect on inefficiency, although several of them are insignificant. As observed by Thursby and Kemp (2002) the insignificance of several inputs is probably due to their being imperfect measures of the effort expended in knowledge transfer activity, since they are used in the production of other university outputs at the same time**.** Outputs all have, as expected, a negative and significant effect on inefficiency. As a robustness check, we have run the same regressions only using the significant variables in models (1) (column (2)) which confirms their significance. Including the squared terms does not change the results and the squared terms themselves are not significant.

Table 4. Regression of inputs and outputs on the *INEFFICIENT* variable

VARIABLES	(1)	(2)
FCGRANTS	0.000	
	(0.000)	
KTSTAFF	0.025^{+}	0.009
	(0.015)	(0.009)
SCIMEDSTAFF	0.002	
	(0.002)	
ENGTECHSTAFF	0.016***	0.012***
	(0.006)	(0.004)
SOCBUSSTAFF	0.008*	0.005^{+}
	(0.004)	(0.003)
ARTHUMSTAFF	0.005^{+}	0.005**
	(0.003)	(0.002)
RESCONSULT	-0.001	
	(0.000)	
IPDISCL	-0.102***	-0.060***
	(0.034)	(0.017)
CPD	0.000*	0.000^{+}
	(0.000)	(0.000)
EVENTS	-0.002**	-0.001**
	(0.001)	(0.001)
Constant	-2.828**	-2.401***
	(1.193)	(0.912)
Observations	80	80
Wald Chi-Square	53.67***	48.85 ***
Pseudo R2	0.661	0.618

Standard errors in parentheses
$^{+}$ p<0.15, *** p<0.01, ** p<0.05, * p<0.1

4.3. The impact of institutional and external factors on efficiency

We also regress the variable capturing the institution's inefficiency on some institutional and external factors. We have estimated two versions of the model, one with the binary dependent variable *INEFFICIENT* (model 1), and one where the dependent variable are the efficiency scores themselves (model 2). In model 2, the efficiency scores have been corrected to take into account the bias arising from the serial correlation of the errors, following the methodology proposed by Simar and Wilson (2007), and the estimates have been obtained through a truncated regression. The standard errors and confidence intervals of the coefficients have been computed following the bootstrap method proposed Simar and Wilson (2000 and 2007); following these authors, we have computed 2000 repetitions to obtain a bootstrapped sample from which to derive the parameters' distribution. The efficiency scores are measured using the Farrell-Debreu distance, with 1 indicating efficient units and values greater than 1 indicating progressively less efficient units.

Both models use the same regressors[11]. The total income accrued from knowledge transfer activities (*TOTKTINCOME*) aims to test whether the scale of the knowledge transfer operations of the institution affects its efficiency; we also consider the square of this variable (*SQTOTKTINCOME*). The diversity of the sources of knowledge transfer income (*KTINCOMEDIV*)[12] aims to test whether engaging in a more diverse portfolio of activities has a bearing on efficiency. Several variables capture institutional characteristics: *HIST* is a dummy that captures whether the university was founded before the mid-Twentieth century; *POLY* is dummy that captures whether the university is a former polytechnic (the reference category are universities founded after the mid-Twentieth century that are not former polytechnics); *PSCIMED, PTECH, PSOC* and *PARTHUM* are the shares of academic staff in, respectively the natural sciences and medicine, technical and engineering subjects, the social sciences and business, and the arts and humanities; *ACADDIV* is the subject diversity of academic staff[13]; *AGE* is the age of the institution, and *TTOAGE* is the age of its TTO. Several variables try to capture the orientation of the institution towards teaching, research and knowledge transfer activities: *RES_INTENSITY* is the

[11] To ensure convergence of the truncated regressions, we have rescaled all regressors to be comprised between zero and 1, as recommended by Wilson (2008).
[12] Measured as the inverse of the Herfindahl index on the shares of income from each source of knowledge transfer.
[13] Measured as the inverse of the Herfindahl index on the shares of academic staff in each subject area (considering four main areas: natural sciences and medicine, engineering and technology, social sciences and business, arts and humanities).

research intensity of the institution, measured as the ratio between funding for research and funding for teaching, *STUDPP* is the number of students per academic staff, *KT_OR* is the ratio between knowledge transfer staff and academic staff, and *SRES_STUD* is the ratio of research students to undergraduates. Finally we control for regional gross value added per capita in 2006 (variable *GVAREG*, available from the UK's Office for National Statistics (ONS), 2006). We do not control for ownership as the universities in our sample are all public. The correlations between the regressors are reported in Appendix B. The analyses are performed on 78 universities, having manually removed two outliers.

In model 1, the logit regression focuses on the likelihood to be inefficient in knowledge transfer. Universities that have greater overall knowledge transfer income (as measured by *TOTKTINCOME*) are more likely to be inefficient, and the quadratic term *SQTOTKTINCOME* is significant with a negative sign, suggesting both universities with very small and very large knowledge transfer income are less likely to be inefficient. Former polytechnics, universities with a greater share of academics in natural sciences and medicine, engineering and technical subjects and the arts and humanities, and universities with diverse subject composition (*ACADDIV*) are more likely to be inefficient, while universities with a greater share of academics in the social sciences and business are more likely to be efficient. The ratio of students on academic staff (*STUDPP*) has a negative effect on the likelihood to be inefficient, suggesting that teaching and knowledge transfer activities are not necessarily in competition with each other. Unexpectedly, universities in regions with greater GVA per capita are more likely to be inefficient; this may reflect the more intense competition between universities for knowledge transfer engagements such as research and consultancy contracts and CPDs, as universities tend to concentrate in historically more prosperous regions.

Table 5. Regression analysis on various specifications of inefficiency using institutional and external factors

Variables	Model (1a)	Model (1b)	Model (2a)	Model (2b)

HIST	0.213	0.213	1.302	1.313
	(1.278)	(1.278)	(1.686)	(1.755)
POLY	1.698+	1.698+	1.510	1.487
	(1.125)	(1.125)	(1.456)	(1.519)
PSCIMED	16.736**		20.326**	
	(6.850)		(9.293)	
PSOC		-16.736**		-19.326**
		(6.850)		(8.974)
PTECH	15.983**	-0.753	9.015	-11.665
	(7.013)	(4.978)	(9.939)	(8.707)
PARTHUM	18.643***	1.908	21.213**	0.656
	(7.202)	(3.513)	(9.521)	(6.237)
ACADDIVR	15.560***	15.560***	25.451***	25.623***
	(5.008)	(5.008)	(6.788)	(7.254)
TOTKTINCOMER	13.078**	13.077**	-1.644	-2.079
	(6.376)	(6.376)	(8.656)	(8.928)
SQTOTKTINCOMER	-14.713**	-14.713**	-2.324	-1.446
	(7.286)	(7.286)	(11.413)	(11.925)
KTINCOMEDIVR	2.093	2.093	2.280	2.472
	(2.653)	(2.653)	(3.399)	(3.693)
RES_INTENSITYR	-4.564	-4.564	-9.050	-9.498
	(5.821)	(5.821)	(8.644)	(9.430)
STUDPPR	-6.666*	-6.666*	-3.761	-4.268
	(3.830)	(3.830)	(4.627)	(4.895)
SRES_STUDR	4.714	4.714	13.608	13.570
	(5.991)	(5.991)	(10.027)	(10.351)
KT_ORR	-3.823	-3.823	1.291	1.078
	(3.287)	(3.287)	(4.219)	(4.211)
AGER	-5.730	-5.730	-3.101	-3.230
	(5.231)	(5.231)	(5.043)	(5.436)
TTOAGER	0.387	0.387	3.416	3.189
	(2.521)	(2.521)	(4.576)	(4.785)
GVAREGR	3.638**	3.638**	6.194***	6.415***
	(1.713)	(1.713)	(2.134)	(2.279)
Intercept	-20.653***	-3.917	-30.694***	-10.615+
	(7.175)	(3.762)	(10.245)	(6.864)
Observations	78	78	78	78
LR Chi2	43.85	25.830	43.85	23.250
d.f.	16	16	16	16
Pr(> chi2)	0.0002	<0.1	0.0002	<0.1

Standard errors in parentheses; $^{+}$ p<0.15, *** p<0.01, ** p<0.05, * p<0.1

In Model 2, a truncated regression is performed on a continuous dependent variable (the bias-corrected efficiency scores), and the standard errors are computed through a bootstrap procedure in order to account for the bias arising from the serial correlation of the error terms. With this approach, we are focusing on the determinants of relative inefficiency rather than on the simple probability to be inefficient. The signs of the coefficients do not change in Model 2 (apart from the coefficient of *KT_OR*, which is however never significant), but the significance of some coefficients does. In particular, the scale of a university's knowledge transfer operations (*TOTKTINCOME*), its squared term (*SQTOTKTINCOME)* and the ratio of students on academic staff (*STUDPP*) are no longer significant. Like in Model 1, having a higher share of academic staff in the natural sciences and medicine and in the arts and humanities increases inefficiency, and so does having a diverse subject composition; the share of academic staff in the social sciences and business reduces inefficiency, and regional GVA has a positive effect on inefficiency.

We do not find evidence that a larger scale of knowledge transfer operations, proxied by the institutions' income from knowledge transfer, is linked to greater efficiency, rather there seems to be a U-shaped relationship so that very small and very large institutions are more likely to be efficient. As can be seen from Figure 3, where the scores here are reported as efficiency rather than inefficiency (efficient universities have a score of 1), many efficient universities operate on a small scale, although some universities operating on a very large scale are efficient, and many universities operating on a small scale are very inefficient.

Interestingly, in the United Kingdom the Higher Education Funding Council for England (HEFCE) has recently (2001) established a permanent stream of funding to reward the institutions that achieve the best knowledge transfer performance; while funds were initially allocated competitively, they are now distributed according to a formula that rewards the universities that have accrued the highest amount of income from several knowledge transfer activities. Our findings do not suggest that institutions that achieve greater income from knowledge transfer activities are more efficient than smaller ones – that is, a unit of input employed in institutions with a larger scale of knowledge transfer operations does not necessarily generate more output than a unit of input employed in institutions with smaller operations. Hence, while larger income from knowledge transfer activities may signal larger impact

(HEFCE, 2011)[14], it is not per se a measure of efficient knowledge transfer performance.

Figure 3. Plot of efficiency scores vs. total income from knowledge transfer

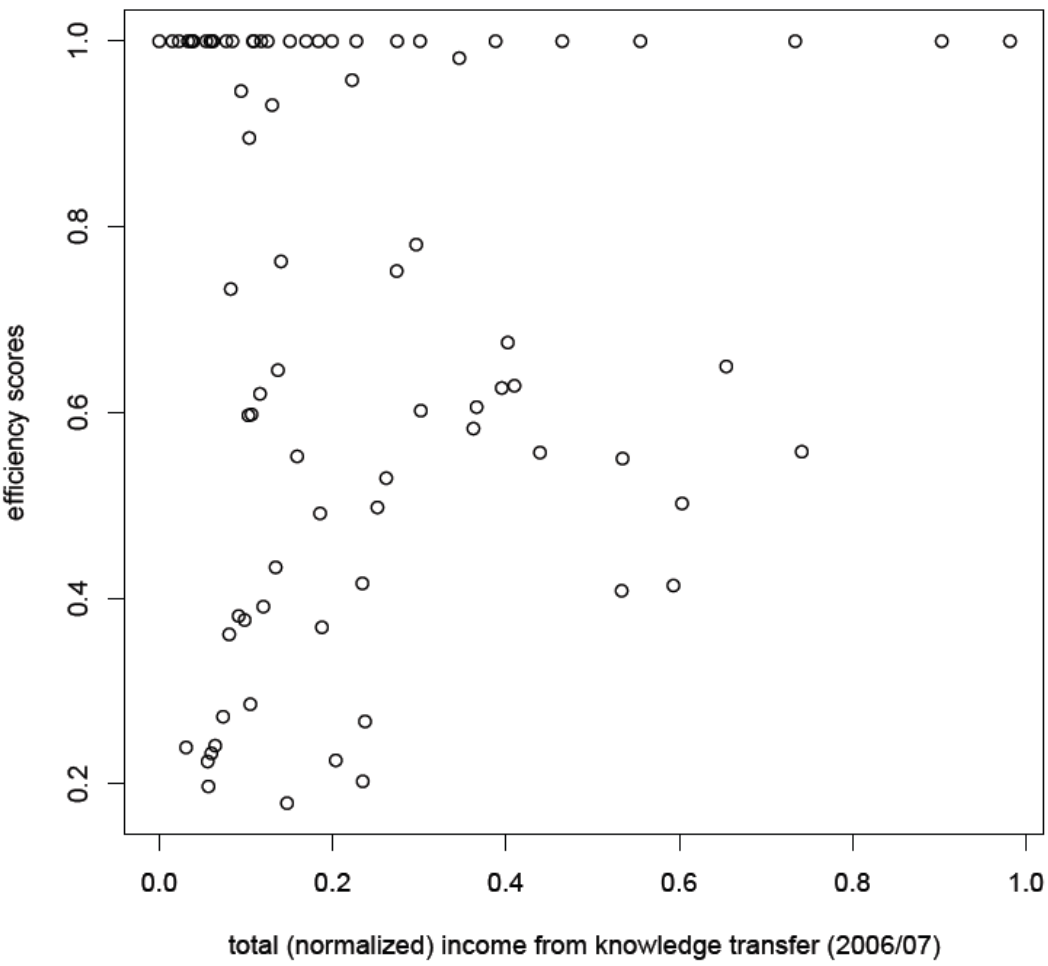
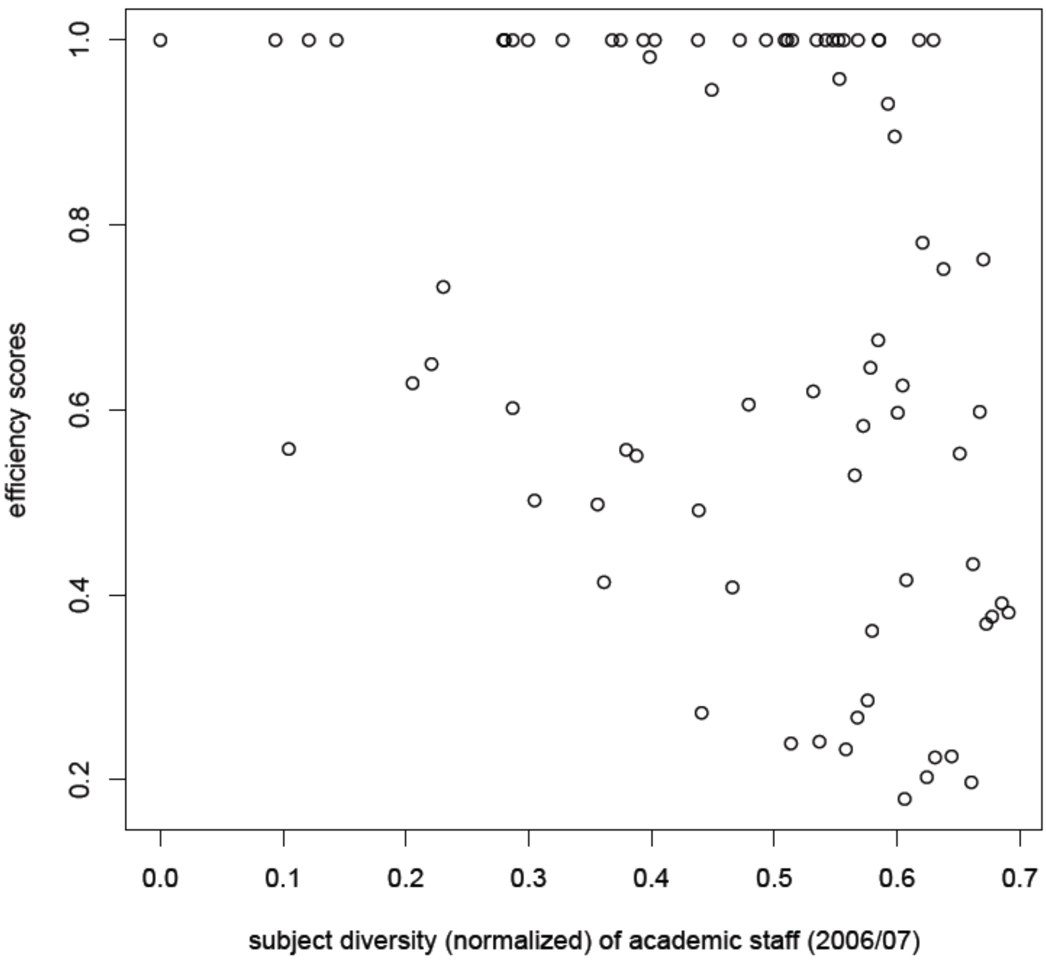


Figure 4 plots diversity in subject composition against the inefficiency scores. We can see that more diverse institutions tend to be more inefficient.

[14] That income of knowledge transfer is an accurate measure of impact is actually debatable, as the prices paid for university services often do not reflect their actual economic and social value (a point made, for example, by the UK's University Alliance in response to a HEFCE consultation in 2011). It is however very difficult to quantify the impact of knowledge transfer activities using other indicators: there is no clear theory of how to measure the impact of the various types of universities' knowledge transfer activities, and data to support this are rarely collected. In this paper, we do not deal with the issue of measuring the "impact" of knowledge transfer, rather we focus on the efficiency implications of adopting different ranges of outputs of the knowledge transfer process, and on the determinants of efficiency.

Figure 4. Plot of inefficiency scores vs. subject diversity of academic staff



5. Conclusions

The current literature on the efficiency of universities' knowledge transfer activities adopts a rather narrow view of knowledge transfer, mainly interpreted as the transformation of research results into intellectual property or as the transformation of patents into licenses. This model of knowledge transfer is appropriate to a small set of academic disciplines and institutions. In this analysis we have adopted a broader approach to knowledge transfer, focusing on a range of outputs that comprises intellectual property disclosures, research and consultancy contracts, continuing professional development courses, and public events. We find that universities that have a greater share of staff in the social sciences and business, and former polytechnics, which perform a variety of knowledge transfer activities, display relatively greater efficiency when outputs are measured in terms of a broad range of activities. Adopting a broader view of knowledge transfer allows us to appreciate that some universities that do not focus mainly, or exclusively, on the filing and commercialization of intellectual property, are efficient in deploying their generic inputs in order to produce knowledge transfer outputs.

When efficiency is measured in terms of a broad range of outputs, universities with a greater share of staff in the social sciences and business are more efficient. We find that specialization (in terms of subject composition) increases efficiency in knowledge transfer, while the scale of knowledge transfer operations has no significant bearing of relative efficiency, although some universities that have very small and very large scales of operations are efficient. We find no evidence of a reduction in knowledge transfer efficiency due to having a larger number of students per academic staff (indeed, this variable has a weakly negative impact on the likelihood to be inefficient), or of performing a larger amount of research relative to teaching, suggesting that knowledge transfer is not competing with teaching and research activities.

The present analysis has several limitations, mainly related to the difficulty in finding ways to identify precisely the inputs that are used in knowledge transfer, and in finding reliable data on the full range of knowledge transfer activities that universities engage in; while this study considers a broader range of activities than previous research, it still omits numerous important areas of engagement (for example, providing certification, testing and prototyping services; organizing student placements in industry; many types of interactions with the local community and the general public). Moreover the measurement of efficiency is only focused on the amount of activities performed and not on their importance, or value. The use of SFE techniques could enrich our understanding of the universities' efficiency in this regard: by focusing on the set of knowledge transfer activities for which information about monetary income exists, it would be possible to study the relationship between use of inputs and generation of income from knowledge transfer activities. Further research should also seek to improve the treatment of outliers, for example by focusing on the computation of order-*m* efficiency scores and the effect of institutional and environmental variables.

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Appendix A. Correlation matrix between inputs and outputs

	FCGRANTS	*KTSTAFF*	*SCIMEDSTAFF*	*ENGTECHSTAFF*	*SOCBUSSTAFF*	*ARTHUMSTAFF*	*IPDISCL*	*RESCONSULT*	*CPD*
FCGRANTS	1.00								
KTSTAFF	0.15	1.00							
SCIMEDSTAFF	0.87	0.12	1.00						
ENGTECHSTAFF	0.75	0.18	0.68	1.00					
SOCBUSSTAFF	0.64	0.09	0.51	0.53	1.00				
ARTHUMSTAFF	0.64	0.18	0.42	0.29	0.50	1.00			
IPDISCL	0.15	0.15	0.17	0.09	0.17	0.08	1.00		
RESCONSULT	0.69	0.14	0.82	0.72	0.53	0.24	0.18	1.00	
CPD	0.07	0.08	-0.03	-0.06	0.16	0.29	-0.01	-0.06	1.00
EVENTS	0.52	0.06	0.47	0.49	0.46	0.51	0.10	0.49	0.10

Appendix B. Correlation matrix between regressors

	HIST	POLY	PSCIMED	PSOC	PTECH	PARTHUM	ACADDIV	TOTKTINCOME	SQTOTKTINCOME	KTINCOMEDIV	RES_INTENSITY	STUDPP	SRES_STUD	KT_OR	AGE	TTOAGE
HIST	1.00															
POLY	-0.55	1.00														
PSCIMED	0.69	-0.46	1.00													
PSOC	-0.54	0.46	-0.58	1.00												
PTECH	-0.39	0.26	-0.42	0.16	1.00											
PARTHUM	-0.25	0.10	-0.60	-0.2	-0.29	1.00										
ACADDIV	-0.61	0.55	-0.64	0.65	0.45	0.08	1.00									
TOTKTINCOME	0.60	-0.35	0.59	-0.45	-0.15	-0.36	-0.53	1.00								
SQTOTKTINCOME	0.54	-0.33	0.55	-0.43	-0.14	-0.33	-0.52	0.95	1.00							
KTINCOMEDIV	-0.27	0.13	-0.19	0.21	0.16	-0.02	0.30	-0.31	-0.31	1.00						
RES_INTENSITY	0.67	-0.57	0.67	-0.52	-0.24	-0.35	-0.64	0.79	0.81	-0.41	1.00					
STUDPP	-0.68	0.54	-0.69	0.47	0.29	0.37	0.63	-0.67	-0.60	0.27	-0.81	1.00				
SRES_STUD	0.66	-0.54	0.65	-0.50	-0.18	-0.39	-0.61	0.81	0.84	-0.39	0.96	-0.79	1.00			
KT_OR	-0.28	0.36	-0.29	0.09	0.22	0.16	0.12	-0.23	-0.22	0.04	-0.35	0.36	-0.35	1.00		
AGE	0.42	-0.21	0.35	-0.26	-0.20	-0.14	-0.29	0.49	0.61	-0.27	0.60	-0.39	0.65	-0.22	1.00	
TTOAGE	0.23	-0.12	0.30	-0.29	0.04	-0.22	-0.29	0.22	0.17	-0.17	0.24	-0.30	0.28	-0.08	0.14	1.00
GVAREG	-0.04	-0.07	0.00	0.06	-0.12	0.05	-0.10	0.12	0.14	-0.31	0.19	-0.01	0.12	-0.15	0.08	-0.08