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An evaluation and explanation of (in)efficiency in higher education institutions in Europe and the U.S. with the application of two-stage semi-parametric DEA

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ABSTRACT

This study uses data envelopment analysis (DEA) to evaluate the relative efficiency of 500 higher education institutions (HEIs) in ten European countries and the U.S. for the period between 2000 and 2010. Efficiency scores are determined using different input-output sets (inputs: total revenue, academic staff, administration staff, total number of students; outputs: total number of publications, number of scientific articles, graduates) and considering different frontiers: global frontiers (all HEIs pooled together) and a regional frontier (Europe and the U.S. having their own frontiers). Changes in total factor productivity are assessed by means of the Malmquist index and are decomposed into pure efficiency changes and frontier shifts. Also investigated are the external factors affecting the degree of HEI inefficiency, e.g. institutional settings (size and department composition), location, funding structure (using two-stage DEA analysis following the bootstrap procedure proposed by Simar and Wilson, 2007). Specifically, it is found that the role of the university funding structure in HEI technical efficiency is different in Europe and in the U.S. Increased government funding is associated with an increase in inefficiency only in the case of European units, while the share of funds from tuition fees decreases the efficiency of American public institutions but relates to efficiency improvements in European universities.

Keywords: Higher education institutions, efficiency, two-stage DEA

Jel Classifications: I23, C14, I22

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1. Introduction

Numbers are meaningful: according to the Academic Ranking of World Universities[1] 2013, eight of the top ten universities were in the U.S., Americans published 25% of the total number of scientific articles in 2013, including 34% of the most cited[2], and approximately 70% of Nobel Prize winners were affiliated to universities in the U.S. Because of this, it is not surprising that the American system of higher education is perceived to be preeminent (especially from the perspective of European countries) and when higher education institutions (hereafter, HEIs) around the world are searching to improve their performance they look to universities in the United States as their benchmark model, while scholars from the whole world are attracted to US academia (Altbach et al., 2013). However, from the internal American perspective, the higher education sector is not free of problems, and its worldwide dominance has also recently been challenged (Altbach et al., 2011)[3]. Nowadays, HEIs in both continents are under pressure due to declining public support, resulting in the need to seek external resources and to provide first-class teaching and research in order to survive amid local and global competition.

This study has three aims: firstly, to compare the technical efficiency of European and U.S. higher education institutions in order to check whether the leading role of the U.S. can be confirmed through strict quantitative analysis. Secondly, to conduct a time-series analysis to contrast total factor productivity (hereafter, TFP) changes in European universities with public American ones. The third aim is to evaluate the main factors that determine the efficiency of HEIs and to test whether these factors might have varying impacts on the level of European and U.S. efficiency.

I employ data envelopment analysis (DEA) – a methodology which constructs a production frontier in the multi-input/multi-output case – in order to evaluate the relative efficiency of a sample of 500 higher education institutions (in ten European countries and the U.S.) for the period between 2000 and 2010. Different versions of the DEA model are estimated for different input-output sets (inputs: total expenditure, academic staff, administration staff, total number of students; outputs: number of articles, publications other than scientific articles, graduates) and assumed frontier: global frontiers (all HEIs pooled together) and a regional frontier: a European versus a US frontier. The latter assumption of a regionally-specific frontier

[1] http://www.shanghairanking.com/ARWU2013.html
[2] http://www.scimagojr.com/
[3] The main problems of the U.S. higher education sector (rising tuition fees and a low level of college attainment) have also been addressed by political actions e.g. Obama announced in August 2013 a reform with the aim of increasing affordability for students and accountability for colleges. The plan aims to measure college performance through a new rating systems (better transparency for students and parents), to tie financial aid directly to college performance and to promote innovation and competition in order to combat rising costs (see more at: http://www.whitehouse.gov/issues/education/reform)

can be justified on the basis of the great heterogeneity of higher education systems in Europe. However, if we take into consideration that nowadays research and teaching activities are globalized (e.g. publications in international journals; researchers competing for international grants, academic staff members and students being more and more mobile), then the assumption of one common global frontier might also be justified.

The research is motivated by the fact that most previous studies have only considered one or a limited number of countries, mainly due to the fact that micro data on HEIs (at the level of individual institutions) are not easily obtainable and comparable across countries and time periods. Few studies have looked at the efficiency and productivity of HEIs from the international perspective. In particular, the efficiency of Italian universities has been compared to that of those in the U.K. (Agasisti and Johnes, 2009), Spain (Agasisti and Perez-Esparrells, 2010) and Germany (Agasisti and Pohl, 2012). However, as these authors admit themselves, general conclusions cannot be drawn on the basis of comparisons between the performances of HEIs in only two countries. Bonaccorsi et al. (2007a) cover universities in Italy, Spain, Portugal, Norway, Switzerland and the UK. Bonaccorsi et al. (2007b) compare universities by research field in Finland, Italy, Norway and Switzerland. They concentrate on testing economies of scale and scope. Finally, Wolszczak-Derlacz and Parteka (2011) analyse institutions in seven European countries for the period 2001 to 2005 and conclude that more efficient universities have a larger number of different departments, a larger proportion of females among the academic staff, a higher percentage of funds from external sources, and are older.

However, unlike the present paper, none of these studies compare the efficiency of European HEIs with their U.S. counterparts or examine differences in performance measured over a 10-year period of time taking into account cross-country and cross-unit heterogeneity.

Taking into consideration the limitations of the previous analyses (limited country and time coverage), here an empirical study of 500 HEIs from eleven countries is proposed, 10 of which are in Europe, for the period between 2000 and 2010. The paper is not limited to evaluating DEA scores but continues with a second step in which the direction and magnitude of the impact of their potential determinants are quantitatively assessed. To the best of the author's knowledge, this is one of the first attempts at cross-country analysis to consider so long a time frame and the first paper to analyse efficiency differentials between European and US higher education institutions together with the role of their different external determinants from both between- and within-country perspectives.

Additionally, the present paper is one of the first studies to apply tools based on resampling methods that allow the assessment of the statistical significance of the results obtained (traditionally, a lack of statistical interference constitutes the main criticism of non-parametric methods). Specifically, following the bootstrap procedures proposed by Simar and Wilson (1999, 2000, 2007) I calculate unbiased DEA scores, then test whether changes in the productivity of HEIs based on Malmquist indices are statistically significant, and finally, in a second stage, through applying a bootstrapped truncated regression I obtain unbiased beta coefficients quantifying the relationship between a given external variable and previously estimated efficiency scores.

The results indicate that European and U.S. institutions are relatively inefficient, with a high heterogeneity of efficiency scores both between and within countries. Based on mean values, it can be said that inefficiency is lower for U.S. institutions compared to the mean value for the whole of Europe, although higher in relation to some specific examples of European countries (e.g. the U.K.). On average, inefficiency decreases over time for the European sample and is stable for the U.S. The main findings of the second-stage analysis are: (a) funding structure matters for technical efficiency but the direction of the effect varies between the European and U.S. sample; (b) a greater inefficiency of universities with a larger proportion of revenue obtained from government resources is confirmed only in the case of the European sample. The share of tuition fees is inversely correlated with the efficiency of U.S. public institutions and positively with that of European ones; (c) the number of different departments is positively associated with efficiency – indicating the presence of economies of scope and/or economies of scale, both for European and US institutions; (c) universities located in wealthier regions of Europe and the U.S. are more efficient.

The remainder of this paper is structured as follows: in Section 2 I very briefly present a methodological basis for the non-parametric analysis of technical efficiency. Section 3 is dedicated to a literature review of empirical studies in which DEA has been applied to evaluating the efficiency of HEIs. Because of the aim of this study, I focus here on cross-country studies. Next, in Section 4, I describe our panel and data, along with key descriptive statistics on the HEIs in the sample. In Section 5, I evaluate different versions of unbiased DEA scores for different input-output sets and assumed frontiers, with an additional assessment of changes in productivity over the period of time analysed. In Section 6, the second-step analysis is conducted, in which I treat the (previously estimated) efficiency scores as dependent variable in a regression equation. I investigate how differences in institutional setting (size, department composition), location and funding structure potentially affect the technical efficiency of HEIs. In order to test whether these factors are similar (in direction and strength) across the European and U.S. samples, the analysis is conducted for these two subgroups separately. Finally, Section 7 concludes.

The results of this study have straightforward policy implications, especially if we take into account the decline in government funding of public higher education and the general budget cuts for public services due to the global financial crisis. Specifically, I show that funding mechanisms have the potential to significantly alter the nature and efficiency of higher education providers, which should be borne in mind by policy makers.

2. Using two-stage DEA to evaluate technical efficiency and its determinants

In the empirical part of this study the technical efficiency of HEIs will be evaluated through non-parametric DEA analysis, and then by regressing efficiency scores on potential covariates. There is much support for DEA methodology for the empirical evaluation of the production of multi-input/multi-output units, which is in fact a characteristic of the activities carried out by HEIs. Turning to a formal presentation of the method, I elaborate here only on an output-oriented model with the assumption of variable returns to scale (VRS), since such a model will be used in the empirical part of the analysis[4]. I closely follow the notation of Simar and Wilson (1999. 2000 and 2007).

The process of production of a given decision-making unit (DMU) (e.g. a university) is constrained by the production set Ψ of physically possible points (x, y) :

$$\Psi = \{(x, y) \in R_{+}^{N+M} \mid \text{x can produce y}\}, \tag{1}$$

where x represents a vector of N inputs, and y a vector of M outputs. The boundary of Ψ is the locus of optimal production plans (production frontier) and in the case of output-oriented efficiency $\partial Y(x)$ is defined as:

$$\partial Y(x) = \{y \mid y \in Y(x), \lambda y \notin Y(x), \forall \lambda > 1\}. \tag{2}$$

The measure of efficiency is found by maximizing achievable output for a given level of the inputs:

$$\lambda(x, y) = \sup\{\lambda \mid (x, \lambda y) \in \Psi\}. \tag{3}$$

Banker et al. (1984) develop a DEA estimator allowing for variable returns to scale (VRS) with linear programming:

[4] For a thorough presentation of different DEA models together with their mathematical exposition see e.g. Coelli et al., 2005; Cooper et al., 2004.

$$\hat{\lambda}_{VRS}(x,y) = \sup\left\{ \begin{array}{l} \lambda \left| \lambda y \le \sum_{i=1}^{n} \gamma_i y_i ; x \ge \sum_{i=1}^{n} \gamma_i x_i \text{for}(\gamma_1,...\gamma_n) \right. \\ \text{such that} \sum_{i=1}^{n} \gamma_i = 1 \quad \text{and}\, \gamma_i \ge 0, i = 1,..., n \end{array} \right. . \tag{4}$$

If the DEA efficiency score is $\hat{\lambda}=1$ (100%), then the DMU is said to be efficient, if $\hat{\lambda}>1$ (or 100%) then the unit is inefficient and the magnitude of the inefficiency is determined by the distance to the frontier (the greater the difference between the DEA score and 1, the greater the inefficiency).

One of the disadvantages of the DEA approach is a lack of statistical interference, which can be overcome by a bootstrap procedure which involves the generation of pseudo-data and the approximation of the unknown distribution of the efficiency scores using the distribution of the bootstrap values (Simar and Wilson, 2000). The biased corrected estimator can be calculated as:

$$\hat{\hat{\lambda}}_{DEA}(x,y) = 2\hat{\lambda}_{DEA}(x,y) - B^{-1}\sum_{b=1}^{B} \hat{\lambda}^{*}{}_{DEA\,b}(x,y), \tag{5}$$

where B is the number of bootstrap replications and $\hat{\lambda}^{*}{}_{DEA\,b}(x,y)$ are the bootstrap efficiency scores.

To assess the efficiency changes of given units between two periods of time (t_1) and (t_2), Malmquist indices (MI) are calculated which are based on the DEA scores described above. In particular, the Malmquist index is computed as the geometric mean of two indices: the first with period t_1 being the reference technology, the second with period t_2 being the reference:

$$MI_{i,(t_1,t_2)} = \left[\frac{D_i^{t}(x_{t_2}, y_{t_2})}{D_i^{t}(x_t, y_t)} * \frac{D_i^{t_2}(x_{t_2}, y_{t_2})}{D_i^{t_2}(x_t, y_t)} \right]^{1/2} , \tag{6}$$

where D_i refers to the efficiency distance function of the given DMU *i*, and x and y are inputs and outputs in periods t1 and t2. The distance functions are calculated using an analogous procedure to that described above in eqs. (3) and (4). A value of MI greater than one indicates positive TFP growth; MI smaller than one is a sign of TFP decline; when MI=1 then a conclusion of no productivity change is reached.

According to Färe et al. (1992, 1994), a Malmquist index can be decomposed into two components: a pure efficiency change (TE) – the movement of a given DMU towards or away from the frontier, and a technology change (TT) – a frontier shift:

$$MI_{i,(t_1,t_2)} = \underbrace{\frac{D_i^{t_2}(x_{t_2}, y_{t_2})}{D_i^{t_1}(x_{t_1}, y_{t_1})}}_{(TE)} * \underbrace{\left[\frac{D_i^{t_1}(x_{t_2}, y_{t_2})}{D_i^{t_2}(x_{t_2}, y_{t_2})} * \frac{D_i^{t_1}(x_{t_1}, y_{t_1})}{D_i^{t_2}(x_{t_1}, y_{t_1})} \right]^{1/2}}_{(TT)} . \tag{7}$$

This decomposition can be important for the assessment of the main determinants of productivity changes, e.g. in order to test whether universities are catching up with the leading ones or whether the whole sector has undergone a major development.

The statistical properties of the MI and its components are obtained by means of a bootstrap procedure analogous to the one used to obtain bias-corrected DEA scores. In particular, the estimation of confidence intervals makes it possible to draw a conclusion about the statistical significance of total factor productivity (TFP) changes. A (1-α) percent confidence interval can be expressed as:

$$\hat{MI}_{i,(t_1,t_1)} + a^*_\alpha \leq MI_{i,(t_1,t_1)} \leq \hat{MI}_{i,(t_1,t_1)} + b^*_\alpha , \tag{8}$$

where a_α^* and b_α^* define, respectively, the lower and upper bootstrap estimates of confidence interval bounds for the Malmquist index and α (e.g. 10%, 5% or 1%).

The final step of our analysis involves examination of (the direction and magnitude of) the potential determinants (Z) of the previously estimated bias-corrected efficiency scores.

$$\hat{\hat{\lambda}}_i = \alpha + Z_i\beta + \varepsilon_i , \tag{9}$$

where ε_i is a statistical noise with distribution restricted by $\varepsilon_i \geq 1 - \alpha - z_i\beta$. Again, a bootstrap procedure is employed to obtain bias-corrected beta coefficients to overcome the problems arising from the serial correlation of previously estimated scores and a possible correlation of the error term (ε_i) with environmental variables (Z_i).

The second-stage regression can be summarized as follows:

1. Apply maximum likelihood to estimators of $\hat{\hat{\lambda}}_i$ to obtain estimates of $(\hat{\beta}, \hat{\sigma})$ in a truncated regression, where $i = 1,...,n$ is the number of DMUs.

2. Repeat steps 2.1-2.3 *L* times to obtain *b* numbers of bootstrap estimates of $\left\{(\hat{\beta}^*, \hat{\sigma}^*_\varepsilon)_b\right\}_{b=1}^{L}$:

   2.1 For each DMU $i = 1,...,n$, draw ε_i from the left-truncated $(1 - z_i\hat{\beta})$ normal distribution;

   2.2. Use ε_i for each DMUs $i = 1,...,n$ to calculate fitted DEA scores: $\hat{\hat{\lambda}}_i^* = z_i\hat{\beta} + \varepsilon_i$;

   2.3 Apply maximum likelihood to estimators of $\hat{\hat{\lambda}}_i^*$ to obtain estimates of $(\hat{\beta}^*, \hat{\sigma}^*)$ in a truncated regression.

3. Compute the bias-corrected estimator of $\hat{\hat{\beta}}$ as well as the percentile bootstrap confidence intervals at a given level of significance using the bootstrap estimates obtained from the previous step $\left\{(\hat{\beta}^*, \hat{\sigma}_\varepsilon^*)_b\right\}_{b=1}^L$ and the original parameters $(\hat{\beta}, \hat{\sigma})$.

I argue that by utilizing consistent bootstrap methodology at every step of the analysis this study offers an important extension of the existing literature. The procedure to obtain the unbiased DEA scores and test the statistical significance of the Malmquist indices is performed using FEAR 1.15 software (Wilson, 2008); the truncated regressions are estimated in STATA.

3. Empirical studies using DEA to evaluate the efficiency of higher education in more than one country

Since the 80s the DEA method has been applied to assess the efficiency of entities operating in various sectors of the economy. According to a survey of DEA applications covering papers published in journals from 1978 to 2010 indexed by the Web of Science and conducted by Liu et al. (2013), education is among the top-five sectors addressed. This is not surprising if we remember that the first DEA articles, by Charnes et al. (1978, 1981), were dedicated to the evaluation of the efficiency of a large-scale public programme directed at disadvantaged children attending public schools. In this steam of the literature, examination of the higher education sector is also present, albeit with a quantitatively lower representation[5]. Due to the nature of the present empirical analysis, the following literature review is restricted to works considering the evaluation of the efficiency of higher education institutions in more than one country. Table A1 in the Appendix presents the sample of multi-country studies.

In particular, Agasisti and Johnes (2009) examine universities in Italy and the UK between the years 2002/2003 and 2004/2005, finding that UK universities were more efficient, but the Italian ones were improving their technical efficiency while the English ones obtained stable scores. Italian universities have also been compared to Spanish universities (Agasisti and Perez-Esparrells, 2010). This time it turns out that they were more efficient in 2004/2005 (in 2000/2001 the efficiency of Italian and Spanish universities was similar); and to German universities (Agasisti and Pohl (2012). The latter publication confirms the conclusion of the earlier studies of a lower level of efficiency of Italian universities accompanied by a relatively higher productivity growth.

[5] Sav (2012) refers to 21 DEA-related studies of universities, with only three of them employing a two-stage approach. However, he does not provide information about the source of this survey. A search of the DEA bibliographic database (the deabib.org version 0.8.1, accessed on July 27, 2014) returns 67 articles with the key word "education" and 27 with the key words "higher education" out of a total of more than 5000 articles (deabib is the extension for the literature collection used in Gattoufi et al, 2004).

Additionally, the authors conduct a second-stage analysis employing tobit regression and find evidence that the efficiency gains were higher for poorer regions (e.g. southern Italy, eastern Germany); medical faculties and operating in regions with a higher unemployment rate were negatively associated with efficiency and the regional share of employees working in science and technology was positively related.

The next three publications examine the AQUAMETH/EUMIDA dataset[6]. A group of 79 universities in four countries (Italy, Spain, Portugal and Switzerland) is examined by Bonaccorsi et al.(2007a). They focus in particular on the relationship between the size of the unit and its efficiency: economies of scale are confirmed for the efficiency of education (up to a certain level, measured by the number of persons employed) while for research efficiency evidence of decreasing economies of scale is found. Finally, the models for neither education nor research reveal a relationship between the size of the individual unit and efficiency. In Bonaccorsi et al.(2007b), this time the level of analysis is four different disciplines: Engineering and Technology, Medical sciences, Natural Sciences, and Social sciences and Humanities in universities in Finland, Italy, Norway and Switzerland A positive relationship between the size of a unit and efficiency is confirmed for all the disciplines analyzed. Finally, in a recent working paper by Bonaccorsi et al. (2014), the analysis is enlarged to 400 universities in 16 European countries, but refers only to a single year (2008/2009). This confirms that the size (economy of scale) and specialization (economy of scope) of a given university have a statistically significant impact both jointly and separately, showing an inverted u-shape effect on efficiency.

A two-stage analysis is performed by Wolszczak-Derlacz and Parteka (2011) on a set of 259 universities in seven European countries for the period 2001-2005. First, they estimate bias-corrected DEA scores, finding a large variation both within and between countries, then regress them on potential covariates. They show that more efficient universities have a higher number of different departments, a larger proportion of females among the academic staff, a higher percentage of funds from external sources and are older. In their next paper (Parteka and Wolszczak-Derlacz, 2013), they utilize the same set of units to calculate Malmquist indexes and find an average annual growth of 4%.

Entire higher education sectors (where the units of analysis are whole countries) are analyzed by Agasisti (2011) and Aubyn et al. (2009). In the first-mentioned publication, an

[6] AQUAMETH and EUMIDA are projects funded by the European Commission which were intended to create the foundations of a regular data collection on individual HEIs in the EU-27 Member States. As far as the author is aware, these datasets are neither comprehensive nor complete, and in addition are not freely available to researchers outside the consortium (for a detail description of these databases see e.g. Bonaccorsi et al., 2010 and Daraio et al., 2011).

analysis of the performance of 18 OECD countries is conducted, finding that the U.K. and Switzerland are the most efficient. Furthermore, on the basis of a tobit regression, the author postulates a positive correlation between the GDP per capita of a given country and the efficiency of its higher education system only when other control variables are included. In some specifications, the percentage of public funding of tertiary education is negatively correlated with its efficiency. Aubyn et al. (2009) find that the most efficient countries are the UK, the Netherlands, Ireland, Sweden, Finland and Denmark. They show that a good-quality secondary system, output-based funding rules, independent evaluation of institutions and staff policy autonomy are positively related to efficiency.

In contrast, Joumady and Ris (2005) examine the efficiency of universities at the lowest level of aggregation – based on the level of generic and vocational competencies acquired by graduates. The study covers graduates from 209 HEIs in 8 countries.

To the best of my knowledge, there are only two studies concerned with intercontinental (Europe versus the U.S.) analysis of HEI efficiency using the DEA approach. However, both are related to very specific cases and no general conclusion can be drawn. Reichmann and Sommersguter-Reichmann (2006) evaluate the efficiency of 118 university libraries in Australia, Austria, Canada, Germany, Switzerland and the United States, utilizing a specific library-related input/output mix (see Table A1 in the Appendix). They find that non-European libraries are more efficient. Finally, Colbert et al. (2000) determine the relative efficiency of three foreign MBA programmes as compared to seven top-ranking U.S. MBA programmes. However, they find that only one programme is inefficient, which is probably due to the low discriminatory power of such a small number of analyzed units in relation to the number of inputs and outputs[7].

In view of these facts, the present study can be claimed to be the first one considering such a broad cross-country coverage and concentrating on a Europe-US comparison, and thus can partly fill a gap in this literature.

4. Data and key characteristic of HEIs

The empirical analysis here was preceded by the collection and integration of data containing information about inputs and outputs at the level of individual higher education institutions and covering different countries and several years. Due to the lack of such a disaggregated database at the European level, the task was very challenging[8]. Both the European and US higher education sectors are very heterogeneous and in order to guarantee a relative homogeneity of the sample,

[7] According to Dyson et al. (2001), the number of DMUs must be at least $2\times x\times y$, where x is the number of inputs and y the number of outputs.

[8] See footnote 6 about attempts to collect data about individual universities from the EU 27.

the primary focus was put on public institutions (because the private sector differs considerably, e.g. in terms of the legislation under which it operates, funding etc.). In the case of binary systems (e.g. German or Austrian Fachhohschule, applied science HEIs in Finland and in Switzerland) only universities were taken into account, and specialist entities such as military, music and theatre academies were also eliminated from further analysis.

The final sample, which was conditioned by the feasibility of collecting complete data, contains information on 348 universities in ten European countries (Austria, Finland, Germany, Italy, the Netherlands, Poland, Spain, Sweden, Switzerland and the United Kingdom) and 152 in the United States for the years 2000-2010[9]. Individual European countries vary considerably in terms of providing information about HEIs. For example, the Finnish Ministry of Education and the Swedish Higher Education Authority provide detailed data on their websites at the level of individual universities about their personnel and financial resources. For Austria, Germany and Switzerland, the data come from national statistical offices; for Spain from the Spanish Rectors Conference (CRUE); for the Netherlands, data on the number of employees, students and graduates come from the Association of Netherlands Universities (VSNU). However, the financial information has been extracted from the financial reports of individual institutions. The source of data on Italian universities is the National Agency for the Evaluation of Universities (ANVUR). Non-financial data for Polish universities come from publications by the Polish Ministry of Science and Higher Education (Szkoły wyższe – dane podstawowe, issues 2001 to 2011), while the financial data are derived from the individual institution financial reports, which are mandatorily published in the Journal of Laws, Monitor Polski B. A detailed description of the sources of the data is presented in Table A2 in the Appendix.

For the U.S. institutions, data come from The Integrated Postsecondary Education Data System (IPEDS), which is a part of the Institute for Education Sciences within the United States Department of Education. IPEDS covers all higher education institutions in the U.S. (more than 4000) but it was decided to limit the sample to only those classified by the Carnegie Foundation as public 4-year or above institutions conducting research, in order to guarantee comparability with the European sample[10]; for example we excluded two-year community colleges, which are mainly engaged in vocationally oriented education.

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[9] A detailed list of all the universities covered by this study is available from the author on request. Since the DEA methodology requires the same number of institutions with a complete set of variables for every year of the analysis, in the case of missing values a regression imputation procedure was employed (e.g. data for Spanish universities were available only for every second year).

[10] In the U.S. sample, only institutions that provide simultaneous information on revenues, expenditure, student enrolment and graduations are included.

Strenuous efforts have been made to assure the comparability of the variables derived across countries and to guarantee their consistency over time. In particular, the Unesco-UIS/OECD/Eurostat (UOE) 2004 data collection manual and the Frascati manual (OECD, 2002) have been followed.

For example, student enrolments and the number of academic and non-academic staff were expressed as full-time equivalents (FTE), and if the data were unavailable, then calculated by summing the total number of full-time students/staff and adding one-third of the total number of part-time students/staff. Total revenues which were originally reported in national currencies were recalculated into real (2005=100) euros[11]. The total revenues were divided into prime sources (core funding, mainly from governments in the form of teaching or/and operating grants), student fees and third sources (e.g. from investments, donations etc.). The teaching output was measured by the total number of graduates (it was not possible to gather the complete data for bachelor and master students separately, since countries differ in the time of implementation of the BA/MA structure; e.g. in Italy the introduction was in 1999 while in Spain in 2006). The research output is proxied by the number of publications (scientific articles and alternatively the total number of publications other than articles) indexed in the Web of Science of academics affiliated with a given institution[12]. Finally, some of the information (e.g. year of establishment, number of different departments, location) was obtain directly from the web pages of individual HEIs.

Table 1 presents the key descriptive statistics on the institutions in our sample.

[Table 1 about here]

The first column shows the number of publications per academic staff member, which can be treated as a partial measure of scientific productivity. The highest value is achieved by Dutch HEIs, where in the period analysed one academic "produces" on average 1.4 publications per year. This is followed by the U.S. with a value of 1. The lowest values is for Polish universities,

[11] To calculate real revenues in euros, the series were first deflated with CPI(2005) = 100, and then converted into euros using the national currency exchange rate from 2005. This procedure makes it possible to avoid the problem of double deflation.

[12] In order to determine the number of publications of various universities, for the total number of works in which at least one of the authors reported a working place her/his institution was counted for consecutive years during 2000-2010. The query was conducted in February-March 2014 and applied to all types of publications (journal articles, conference papers, reviews, chapters in books, etc.) from all specified indexes (e.g. Science Citation Index Expanded (SCI Ex), Social Science Citation Index (SSCI), etc.).

where on the basis of this indicator it can be said that each academic staff member publishes one piece of scientific work every 5 years on average. Of course, it should be emphasized that these are average values and the variation within countries is considerable, e.g. in the Netherlands for the Rotterdam Erasmus University, the best university in terms of the number of publications per academic in 2010, the indicator equalled 4, and for the weakest unit – the University of Tilburg – below 1. The mean value for the European institutions in the sample is also shown. In the case of publications per academic staff member, the U.S. universities lead. However, when the indicator is expressed as the number of publications by institution revenues (in millions of constant euros) the picture changes. The American dominance vanishes, and in fact America goes into last place now. The Dutch institutions are in first place, followed by German and Italian universities, with Polish HEIs in fourth place now. The improvement in the latter's position reflects the relatively low level of funding of HEIs in Poland, which is confirmed by the relationship of total revenues to students (column 5). In the third column, the number of graduates per academic staff member is presented. This might be interpreted as a partial measure of teaching productivity. It must be remembered that this rate is also dependent on the graduation rate – the number of students who graduate versus dropouts. The highest ratio is for British, Italian and American institutions. The next column presents the average number of students, which shows the size of the units. The largest universities in terms of numbers of students are in Italy and Spain.

In the last two columns, the sources of institutional revenues are presented. The lowest share of funding from primary sources (government) is recorded for universities in the U.K., where only 41% of total revenues come from core funding. In the US, almost 65% of revenues come from the total government appropriations (federal, state, and local), while state funds constitute around 30%.

If we look at the share of the fees paid by students, the highest value is recorded for the U.S., where on average 30% of university income comes from fees paid by students. In Poland, the ratio is 19%, which is quite surprising if we consider that studies at public universities are generally free of charge – the fees come from the part-time students.

A very particular feature of our dataset is its multi-year dimension, which allows us to observe changes in the variables over time. Overall, U.S. universities have many more resources than their European counterparts over the whole period of time. There is a slight increase in revenues per student – shown in Figure 1 – (as well as in revenues per academic staff member, which are not presented here), both for US and European institutions. However, the trend is not common for all European countries; specifically, in Italy, the Netherlands and Sweden there was a drop in the ratio.

Figure 2 presents changes in the share of revenue coming from government resources. In both groups there is a decline in the percentage (in the U.S. the drop is much more pronounced). The drop in the share of revenue from government sources is accompanied by an increase in revenue from tuitions fees (from 20 to 29% for the U.S. and from 12 to 23% for European HEIs).

[Figures 1 and 2 about here]

These changes in absolute and relative resources undoubtedly impacted on the institutions' performance. In the second step of our analysis we will examine how this changed revenue structure influenced technical efficiency.

5. Assessment of higher education institution efficiency using DEA

5.1 Efficiency scores

The critical part of this stage is the definition of the inputs and outputs of university activity. The choice is guided by the state of the art (the inputs and outputs used in previous cross-country studies are reviewed in Table A1 (Column 4) in the Appendix). However, it is also the result of the feasibility of collecting comparable data. The benchmark model considers three inputs: academic staff, total revenue and total number of students; and two outputs: publications and graduates. Alternatively, I calculate a 2-input/2-output model (without students as input) and a 4-input/3-output model (inputs: academic staff, non-academic staff, total revenues, students; outputs: scientific articles, publications other than scientific articles, graduates). Furthermore, I distinguish between two different assumed frontiers: global frontiers (all HEIs pooled together) and European versus US frontiers (European countries pooled together) and consequently evaluate two different versions of the DEA models for each of the input-output sets (Table A3 in the Appendix presents the basic descriptions of the DEA models).

As was shown in the previous section, the sample of 500 HEIs in 11 countries constitutes quite a heterogeneous panel. As suggested by some recent studies (Sarkis, 2007, Daraio et al., 2011), to guarantee a balance of data across and within countries I perform mean normalization of all the inputs and outputs and express them either in relation to the global mean (common frontier) or to the European or US means (region-specific frontier). I proceed with the analysis by evaluating output-orientated efficiency models with variable returns to scale (VRS) for every year between 2000 and 2010.

The first stage DEA results are presented in Table 2 – as country and period means[13]. As can be seen from Table 2, the mean efficiency scores vary greatly between and within the analysed countries. The UK, Poland, the Netherlands and Italy are the most efficient countries with the lowest mean efficiency scores (the lower the score, the higher the efficiency; a score equal to one indicates an efficient unit). The Austrian and Finnish HEIs show the highest mean efficiency scores. The mean value for the whole European sample is 1.61 under the assumption of a common frontier and this drops to 1.51 for the European-US frontier. In both cases the values are greater than for US universities. Since we are assuming an output-oriented approach, an inefficient university would have to increase its output by a factor of (DEA score -1)×100% in order to reach the frontier. Therefore, the efficiency score of 1.56 (1.33) for the US indicates that, taken together with the other universities in the country analysed, they could improve their output as much as by 56% (33%) keeping their inputs stable.

[Table 2 about here]

The kernel distribution of efficiency scores (pooling all years) by country is shown in Figure 3. Most of the countries are characterised by a leptokurtic and skewed distribution with a concentration of mass in the lower tail in the direction of more efficient units. The exceptions are: Austria with the distribution shifted to the less efficient units on the right; Finland and Germany with a flatter distribution; and Spain and Sweden with a rather central distribution. These density estimates appear to graphically support the previous findings of a high variability of efficiency measures within and between countries.

[Figure 3 about here]

This part of the analysis if finished by applying the bootstrap algorithm in order to calculate bias-corrected efficiency scores. The bias-corrected efficiency scores are on average higher than the previous estimates. However, the countries' rankings are sustained and the shape of the distributions follows the previous ones (see Figure 4). DEA exercises were conducted on different DEA models but the results are similar (the Pearson correlation matrix is offered in Table A3 in the Appendix).

[Figure 4 about here]

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[13] The detailed results of the DEA scores for each institution for each year and all the different DEA models are available from the author upon request.

5.2 Changes in productivity and efficiency over time – Malmquist indices

Due to the multi-year dimension of the dataset I am able to not only examine *levels* of efficiency but also to assess *changes* in productivity over time. I calculate Malmquits indices and their components for every institution and year in the sample analyzed for the DEA models specified in the previous section. If the Malmquist index (MI) equals one, it represents a lack of changes in productivity – a value greater than one indicates positive TFP growth, while a MI smaller than one indicates a TFP decline. Table 3 presents the average annual changes in TFP based on the original Malmquist indices[14] for the 11 countries analyzed both for the common frontier and for the European-US ones. The mean values are calculated on the basis of only statistically significant indices (however, the percentage of statistically significant indices is high – between 77% for all the indices in the Netherlands and 90 % in Austria). The statistical significance reflects the fact that unity is not included between the lower and upper bounds of the confidence intervals expressed by eq. 7.

[Table 3 about here]

Interestingly, a rise in TFP is registered on average for the whole European sample (2.6% per year in the case of the common frontier method, 1.5% per year in the case of the region-specific frontier), which was mainly due to changes in technical efficiency (a catching up effect). At the same time, the productivity of American HEIs does not change much; a 1% drop when the global frontier is assumed and a 0.2% rise with the country-specific frontier. Altogether, they experience an increase in technical changes and a decrease in technology development.

Looking at the single European countries, the highest growth was experienced by Dutch and Italian HEIs (an average annual growth of 6%). In both cases it was driven by technical efficiency changes. These are followed by Finnish, German and Swedish institutions, with growth of around 4% per year, again as a consequence of an increase in technical efficiency. Polish and Swiss HEIs improved their productivity by around 2% annually on average, UK ones by 1% and Austria did not experience statistically significant changes in TFP. Finally, Spain is the only European country with a decrease in productivity. All of the indices (except for Spain and the

[14] Bias-corrected Malmquist indices as well as their components were also calculated, but since their mean square error (MSE) was higher than the MSE of the original estimates in most of the cases (91% for MI, 97 for TE, 98 for TT – under the assumption of the common frontier; 93% for MI and 97 for TE and TT under the assumption of a European-US frontier) we do not report them here. The procedure for choosing which Malmquist estimator (and its components) to be used is based on Simar and Wilson, 1999, p.463.

US) are slightly lower when we consider European/US specific frontiers rather than the common one. In the extreme case of the UK, instead of average annual growth of 1% we now obtain a 0.8% decline in productivity.

A further confirmation of the different patterns in productivity changes between HEIs in Europe and the U.S. can be seen in figure 5, where annual changes in TFP are graphically represented for the two subgroups over the period 2000-2010.

[Figure 5 around here]

On average, the US institutions achieved improvements in productivity only in 2000/2001 and 2008/2009; for the rest of the period the indices were below 1, indicating a decline in TFP. On the contrary, in the European sample productivity decreased only in 2001/2002 and 2007/2008. A wider gap in productivity changes is concentrated in the years 2004-2007.

The specific results reported refer to the use of DEA Model 1, but a correlation matrix between the indexes obtained with the different models is presented in the Appendix, and shows that they are qualitatively and quantitatively (Pearson scores) similar (Table A 5).

6. Exploring the determinants of inefficiency

6.1 Empirical specification

In the previous sections of this study, a relatively high level of technical inefficiency of HEIs in Euroepan countries and the U.S. has been shown with a substantial variability in efficiency scores both between and within countries. From the policy perspective, it is interesting to examine the determinants of university efficiency, which can be helpful to answer the question of what can be done to improve it. This will be performed in the second step of the analysis, where the (previously estimated) DEA scores are regressed on potential determinants (describing: institution size, department composition, funding schemes, and country- and region-specific characteristics). In order to check whether the impact (both direction and strength) of these external factors is common for European and US HEIs, the following regression is estimated separately for the two subgroups, elaborating the general eq. (9):

$$\begin{aligned} DEA_{i,t} = {} & \alpha + \beta_1 GDP_{n,t} + \beta_2 DEP_{i,t} + \beta_3 MED_i + \beta_4 TECH_i + \beta_5 FOUND_i + \\ & + \beta_6 REV\_GOV/REV\_FEE + \chi_j + \chi_t + u_{ijt} \end{aligned}, \qquad (10)$$

where: *i* refers to a single HEI, and *t* denotes the time period. The dependent variables are unbiased DEA scores (calculated as in eqs. 4 and 5). They are regressed on potential covariates.

Among the environmental variables we include a proxy for location expressed as GDP per capita of the region *n* (NUTS2) where the institution is located (GDP). For the U.S. sample GDP refers to the state. University location can have an ambiguous impact on performance: if institutions take advantage of a wealthy region (e.g. through cooperation with local business) then there should be a positive correlation between GDP and efficiency; however, it is also possible that universities revitalise poorer regions and an inverse relationship is plausible. For example, Agasisti and Pohl (2012) find that universities in economically disadvantaged regions gain efficiency more rapidly then those in advantaged ones.

Next, I include a variable representing the number of different departments (DEP). This can represent either an economy of scale (larger institutions have more departments) and/or an economy of scope (different departments representing various disciplines). The problem of the potential existence of economies of scale in higher education has been much debated (for a review of relevant studies see Bonaccorsi et al. (2007a). The general conclusion is that larger institutions are more efficient. Some studies have confirmed economies of scale up to a certain level (see Bonaccorsi et al. (2014); after this threshold diseconomies can materialise (e.g. through excessive bureaucracy).

In addition, we introduce a dummy variable equalling one if the HEI has a medical or pharmacy department (MED) to take into account the specificity of faculty composition and the level of cost that these departments can impose. Agasisti and Pohl (2012) show that universities with a medical faculty are less efficient. For similar reasons a dummy variable is also included for technical universities (TECH).

Next, an association between the year when a given institution was established and its efficiency is also tested by employing a variable representing the year of foundation (FOUND). We may expect older institutions to be more efficient (for reasons of tradition and reputation); on the other hand younger units might be more flexible. Breu and Raab (1994) suggest that although universities do expend resources on enhancing their reputation and prestige such efforts do not necessarily result in higher efficiency (measured by student satisfaction).

Finally, we introduce two variables representing the structure of funding: REV_GOV, representing the share of government funding in total revenues; and REV_FEE for the share of tuition fees. Due to a high correlation between these two variables (Pearson coefficient = -0.67) they are introduced in separate regressions. Although the relationship between a university's revenue structure and efficiency is of great importance from a political perspective, the issue has hardly been addressed in previous studies. For Europe, Wolszczak-Derlacz and Parteka (2011) show that the greater the share of core funding the lower the efficiency. In the U.S. context, the association can be different: Robst (2001) finds signs of an inverse relationship between the share of state funds and inefficiency, but without statistical significance when other variables are controlled for. Similar results (the more state funding the higher the efficiency, but again without statistical significance) are obtained by Sav (2012, 2013). He concludes that greater tuition-fee dependency promotes inefficiency in the case of American public universities.

The estimation strategy involves truncated regression (since the DEA scores are equal to or greater than one) and a bootstrap simulation methodology is employed to account for a potential serial correlation of the DEA scores and a possible correlation of the error term with the covariates, as discussed in section 2.

6.2 Results

The results of the benchmark regressions corresponding to the DEA scores for the 3-input/ 2-output model with a common frontier are presented in Table 4 for the European sample, and in Table 5 for the U.S. Since the dependent variables are equal to or greater than one, a positive/negative sign on the estimated regression parameter indicates lower/higher efficiency (higher/lower inefficiency). For each of the subsamples we report three specifications: the first with all the control variables, as discussed in the previous section, except for those representing the funding structure. Next, we add REV_GOV, and in the third specification we substitute it with REV_FEE. In the first columns, the bias-adjusted coefficients from a basic regression are presented. The next two columns show the lower and upper bounds of the 95% bootstrap confidence interval, which is used to check the statistical significance of the estimation by testing whether the value zero falls within the confidence intervals.

[Tables 4 and 5 about here]

I then run two separate regressions: for European institutions and for U.S. ones only. With this exercise I am able to detect the similarities and differences between the impacts of the external variables on the technical efficiency of the institutions from the two distinct continents. In fact, I find a number of similarities but also a couple of noteworthy differences. In all the specifications, the results reveal a negative and statistically significant coefficient for GDP for both the European and U.S. samples, indicating a greater efficiency of universities located in richer regions. Similarly, the statistical significance of the number of different departments is confirmed. The negative parameter in front of the DEP variable shows that HEIs with a greater number of different departments have lower DEA scores (more efficient), which can be a sign of economies of scope. However, it could also be a sign of economies of scale, as larger units usually have a greater number of different departments. This issue will be discussed more thoroughly later. These results hold for both the European and U.S. samples. Finally, technical universities are characterised by greater inefficiency for both groups of HEIs.

A medical faulty is associated with greater efficiency in the case of the European sample but the opposite is true for the U.S.. The year of foundation is statistically significant only in the case of European institutions and its sign indicates that younger units are less efficient – in the case of the U.S. the coefficient is not statistically significant.

Turning to the potential impact of funding structure on the technical efficiency of universities, there are some interesting results. For the European sample (specification (2) in Table 4), the results indicate a positive relationship between the share of funds from government resources and inefficiency. However, this is not confirmed for U.S. institutions, for which the relationship is not statistically significant. In contrast, tuitions fees have a negative impact on the technical inefficiency of HEIs in Europe (specification (3) in Table 4) and a positive one for the inefficiency of units in the U.S. (specification (3) in Table 5). Most of these results are confirmed when the regional frontier is imposed (see Tables A6 and A7 in the Appendix).

To check the sensitivity of the results, the same exercise is repeated for two alternative DEA models. The model with 2 inputs and 2 outputs (without students as an input) is estimated with the inclusion of the variable (STUD) expressed as a log and substituting the variable DEP. In these specifications we obtain a negative and highly statistically significant coefficient indicating that larger units (in terms of student enrolments) have lower levels of inefficiency.

I further explore the robustness of the finding by alternating the estimation methods and the specification per se[15]. For example, a single bootstrap procedure is utilized regressing the 'original' DEA scores on the basis of the bootstrap truncated regression, altering the truncation points (0.999 to 1) and changing the number of bootstrap replications. In the case of the American sample, regional dummies (distinction into 8 geographic regions) are added to the specifications, and alternatively state dummies. In the latter case, the GDP variable loses its statistical significance, which is quite reasonable, but the rest of the results are maintained. Finally, to take into account possible time delays in the impact of the share of government/tuition-fee revenues on efficiency (even though the time series tend to be persistent, and past realizations of

[15] The detailed results for this section are available from the author upon request.

REV_GOV and REV_FEE correlate with the present ones with a coefficient of correlation of 0.94), the regression analysis is altered by including the time-lagged values of the funding structure. The estimation results are very similar to those obtained previously, but in the European model the coefficient on the government revenue share is statistically significant at a lower level.

7. Conclusions and discussion of findings

In this study, DEA – a methodology to construct a production frontier in multi-input/multi-output cases – has been employed in order to evaluate the relative efficiency of a sample of 500 higher education institutions (from ten European countries and the U.S.) for the period between 2000 and 2010. This is the most comprehensive (as far as country, time period and input/output measures) dataset at the level of individual institutions to be employed for this purpose, and the first one composed of countries from different continents (to the best of the author's knowledge). Different versions of the DEA model were estimated with different input-output mixes (inputs: total revenues, academic staff, administration staff, total number of students; outputs: total number of publications, number of scientific articles, graduates) and assumed frontiers: a global frontier (all HEIs pooled together) and a European versus a US frontier (European countries pooled together).

The results reveal a relatively high level of technical inefficiency of HEIs and a substantial variability in the efficiency scores both between and within countries. For European universities, the average technical efficiency score under the assumption of a common frontier is 1.61, suggesting that to become fully efficient with the given inputs, 61% more outputs should have been generated. The score is 1.51 when a region-specific frontier is imposed. The respective values for U.S. universities are: 1.56 and 1.33.

There are different patterns in the total factor productivity changes in the period analysed for the units from Europe and the U.S. The first group of institutions experienced a rise in productivity (average annual growth of 2%) while the HEIs in the U.S. are characterised rather by stable efficiency without changes in productivity.

In a second step of the analysis, the previously-estimated DEA scores were related to their potential determinants (environmental variables), which may be helpful to answer the question of what can be done to improve technical efficiency. Some major differences between the two groups regarding funding structure are evident. As far as the European sample is concerned, a shift to government funding as a revenue source decreases a university's technical efficiency while this relationship is statistically insignificant for the U.S. Furthermore, the results indicate that the technical efficiency of European universities improves with increased dependency on tuition fees as a source of revenue, while it declines in the case of U.S. institutions. For both groups, economies of scale (larger units have higher efficiency) have been confirmed as has a positive impact of location (units located within wealthier regions are more efficient).

It would be interesting to compare the findings here with previous studies, although a direct comparison is problematic due to the sample composition, the years covered, and the model specification (e.g. different input-output sets). The results are in line with Wolszczak-Derlacz and Parteka (2011)'s analysis in which they assess the impact of the share of revenue from core funding (mainly governmental) on the technical efficiency of public universities in seven European countries. For the public U.S. sector, Sav(2012) finds high values of mean inefficiency, which are decreasing with the share of government funding (although the result is statistically insignificant). Similarly, Robst (2001) shows an inverse relationship between the share of state funding and inefficiency, but again the relationship loses its statistical significance when other control variables are added to the specification.

It may seem quite surprising that the leading role of the U.S. has not been confirmed in this study: U.S. institutions are quite inefficient, with efficiency scores slightly below the mean European value, but clearly above the levels that characterise the most efficient countries. A possible explanation may lie in the sample compositions and the exclusion of private institutions from the analysis, which in the case of the American higher education sector are quite successful and have relatively high efficiency (Sav, 2012). However, inclusion of the U.S. private sector would surely have distorted the present analysis and comparison between private and public institutions is beyond the scope of our paper.

Nevertheless, this analysis is a first attempt to compare the technical efficiency of European and U.S. HEIs. Importantly, it has shown distinct differences related to the potential impact of funding schemes on the efficiency of the institutions in these two groups. The question arises of why the share of government funding seems to bring disadvantages in terms of technical efficiency only in the case of European institutions, while it does not hurt the efficiency of their American counterparts. There are some possible explanations. The first of these is connected with the different procedures for obtaining these funds in Europe and in the U.S. For example, most U.S. federal grants are awarded through a competitive process (e.g. on behalf of the National Science Foundation, which distributes funds using merit-based research competitions). Additionally, more and more states have introduced a performance-based procedure to allocate funds among universities. Furthermore, as shown by Aghion et al. (2009), when universities receive a positive funding shock, they become more productive if they are more autonomous and face more competition e.g. from private research universities, as in the U.S. In the case of Europe, increases in government funding without the spur of competition and university autonomy will simply lead to wasteful use of resources. Additionally, the commercialisation of the European HE sector is still at a relatively low level. An increase in this would seem to be beneficial for the unit efficiency.

Some shortcomings of this study need to be admitted, mainly regarding the specification and the limited number of inputs and outputs, which were measured purely quantitatively. As such, no references to the quality of the universities' activity have been made, especially with regard to the teaching. The number of publications and scientific articles indexed in the Web of Science (WoS) does to some extent reflect their quality, since WoS only lists publications with a positive impact factor. A measure of the quality of higher education graduates is, however, much more problematic. In spite of some attempts to overcome this problem, e.g. by utilising employment statistics and by measuring the value added by teaching through comparison of entrance and exit exams, teaching quality measures are not only unavailable on a broad scale but their accuracy is also questionable (Breu and Raab, 1994). Additionally, many of the outputs of educational units are not measurable at all. For example, it is difficult to measure the so-called third mission – a university's contribution to the surrounding community. Consequently, the lack of adequate quality controls and omitted variables can bias the estimation e.g. greater expenditure on quality may have been attributed to inefficiency. However, in the cross-sectional time series analysis this problem should be less severe (Robst, 2001).

Nevertheless, I have examined the effect of variation in inputs and outputs on efficiency scores. Moreover, the adoption of these measures of inputs and outputs in the study was determined not only by the data available, but also by the practices applied in similar analyses. However, I argue that any strict causality between efficiency scores and their potential determinants could be problematic. For example, universities located in better-off regions can take advantage of wealthier surroundings, while it may be the case that efficient HEIs are more successful in revitalising the surrounding area (e.g. by providing a well-educated labour force). Moreover, efficient European universities can attract more third-party funding e.g. tuition fees; on the other hand, universities with a greater share of external funding may benefit from more financial resources and improve their efficiency.

In view of these facts, there is a clear need to create and provide a comprehensive cross-country database at the level of individual institutions (especially at the European level) containing detailed descriptions of the resources of units as well as the results of their activities. The feasibility of collecting such information has been proven by our analysis. Without such a database, further studies of the efficiency of HEIs and its determinates will be highly difficult, while the importance of such studies is high, from the perspectives of university administration, students, and whole economies.

Tables and figures

Table 1. Key statistics on HEIs – mean values by country, time period 2000–2010

country	Publications per academic staff member	Publications per 1 m revenue (in real euros)	Graduates per academic staff member	Total number of students	Revenue per student per year in real euros	Revenue from government funding in % of total revenue	Revenue from tuition fees in % of total revenue
AUSTRIA N=11	0.61 (0.28)	4.21 (1.79)	1.70 (0.75)	19576 (18655)	9606 (4972)	79 (9)	n.a
FINLAND N=13	0.63 (0.33)	4.77 (2.27)	1.56 (0.72)	12176 (8570)	10836 (2808)	65 (7)	n.a
GERMANY N=65	0.55 (0.29)	6.94 (4.75)	1.37 (0.71)	17781 (10689)	9645 (3880)	63 (12)	n.a
ITALY N=54	0.86 (0.40)	5.23 (2.37)	4.51 (1.54)	30143 (25038)	5706 (2356)	81 (7)	14 (6)
NETHERLANDS N=10	1.42 (0.89)	6.62 (2.06)	1.95 (1.20)	17983 (6109)	24517 (5594)	61 (8)	7 (2)
POLAND N=30	0.21 (0.13)	5.41 (2.50)	3.02 (1.06)	21262 (9974)	2346 (797)	65 (7)	19 (8)
SPAIN N=47	0.32 (0.16)	4.90 (2.20)	1.79 (0.42)	28493 (19616)	4239 (1072)	n.a.	n.a
SWEDEN N=24	0.66 (0.68)	3.08 (2.58)	2.69 (1.11)	11099 (7627)	16062 (16264)	72 (11)	n.a
SWITZERLAND N=9	0.91 (0.32)	5.48 (1.53)	0.79 (0.39)	11526 (5444)	31443 (13250)	87 (5)	n.a
UK N=85	0.76 (0.55)	3.84 (2.73)	5.16 (2.03)	18136 (7193)	12436 (7395)	41 (9)	22 (8)
European N=348	**0.64** (0.49)	**4.98** (3.27)	**3.16** (2.10)	**20658** (15732)	**10445** (9013)	**62** (18)	**18** (8)
USA N=152	**1.04** (0.76)	**2.53** (1.77)	**3.90** (1.50)	**21885** (15755)	**26101** (16321)	**64 /30*** (12)/(10)	**30** (12)

Notes: standard deviation in parenthesis. Revenues expressed in real euros, prices from 2005, * state funding

Source: Own elaboration

Table 2 Summary statistics for efficiency measures using a common and European-US frontier

	Global frontier			European - US frontier		
	Mean DEA scores	Std. dev.	Total number of efficient units	Mean DEA scores	Std. dev.	Total number of efficient units
AUSTRIA	2.25	0.41	0	1.93	0.41	6
FINLAND	2.15	0.51	0	1.89	0.39	0
GERMANY	1.82	0.54	52	1.71	0.46	61

ITALY	1.52	0.43	57	1.38	0.32	72
NETHERLANDS	1.51	0.44	9	1.39	0.31	11
POLAND	1.31	0.31	74	1.29	0.29	78
SPAIN	1.85	0.41	9	1.78	0.35	8
SWEDEN	1.85	0.46	22	1.77	0.42	22
SWITZERLAND	1.90	0.31	0	1.81	0.26	0
UK	1.29	0.20	84	1.24	0.17	104
Europe	**1.61**	**0.36**	**307**	**1.51**	**0.26**	**362**
USA	**1.56**	**0.36**	**98**	**1.33**	**0.26**	**180**

Source: Own elaboration

Table 3. Annual changes in productivity (MI), efficiency (TE) and technology (TT) – mean value of statistically significant* indices by country for the period 2000-2010

	Common frontier			European-US frontier		
	MI	TE	TT	MI	TE	TT
AUSTRIA	1.000	1.029	0.972	0.982	0.986	0.995
FINLAND	1.042	1.118	0.979	1.031	1.062	0.996
GERMANY	1.041	1.081	1.012	1.036	1.048	1.018
ITALY	1.061	1.134	0.962	1.042	1.080	0.984
NETHERLANDS	1.059	1.092	1.021	1.056	1.067	1.026
POLAND	1.021	1.043	1.003	1.013	1.032	1.002
SPAIN	0.983	0.983	1.010	0.990	0.980	1.015
SWEDEN	1.039	1.065	1.008	1.023	1.046	0.998
SWITZERLAND	1.025	1.054	1.000	1.015	1.091	0.988
UK	1.011	1.051	0.984	0.992	1.029	0.979
Europe	1.026	1.064	0.993	1.015	1.037	0.997
USA	0.990	1.039	0.965	1.002	1.015	0.996

* significance at 10% level. Results based on the DEA model 1: three-input (total revenues, academic staff, students)/two-output model (publications, graduates).
Source: own elaboration

Table 4 The determinants of inefficiency scores for the European sample – DEA 3-input/2-output model with common frontier

	(1) Bias-adjusted coefficients	95% bootstrap confidence intervals		(2) Bias-adjusted coefficients	95% bootstrap confidence intervals		(3) Bias-adjusted coefficients	95% bootstrap confidence intervals	
		low	high		high	low		high	low
GDP	-0.330***	-0.449	-0.191	-0.357***	-0.491	-0.221	-0.230***	-0.338	-0.129
NOFAC	-0.029***	-0.037	-0.021	-0.025***	-0.033	-0.015	-0.006*	-0.014	0.003
MED	-0.301***	-0.369	-0.230	-0.360***	-0.426	-0.287	-0.028	-0.097	0.044
FOUND	0.083***	0.066	0.100	0.088***	0.067	0.107	0.029***	0.015	0.043
TECH	0.469***	0.383	0.547	0.486***	0.403	0.568	0.248***	0.133	0.346
REV_GOV				0.348**	0.014	0.683			
REV_FEE							-1.321***	-1.77	-0.856

	3826			3088			1576		

Notes: * indicates that the value zero does not fall within the 90% confidence interval, ** indicates that the value zero does not fall within the 95% confidence interval, *** indicates that the value zero does not fall within the 99% confidence interval. Confidence intervals obtained from 1000 bootstrapping interactions.
Constants are not reported. Year and country dummies included in all models.
Source: own calculations

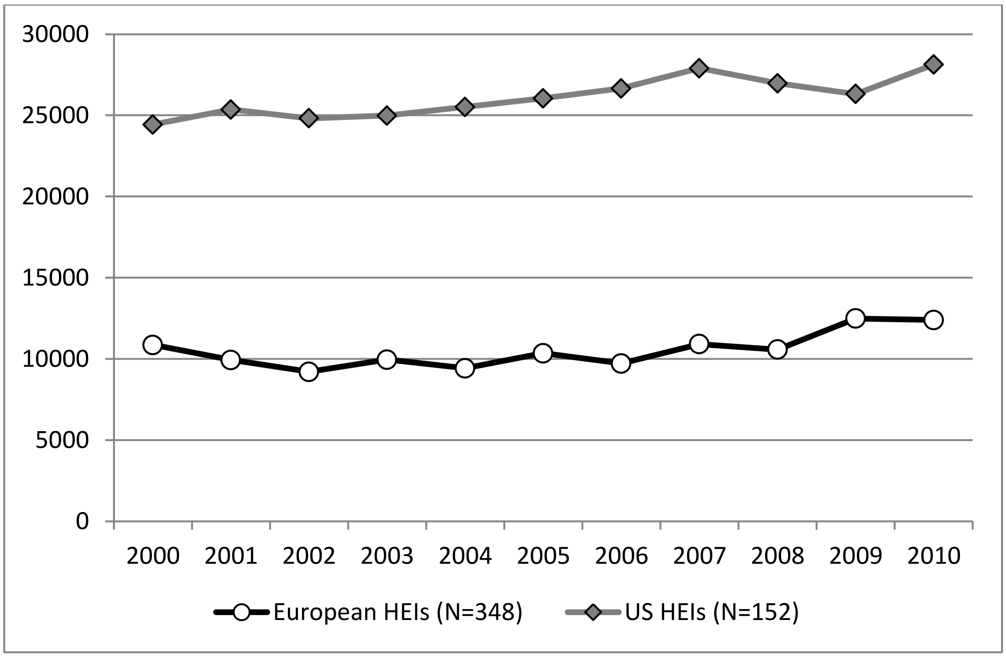
Table 5 The determinants of inefficiency scores for the U.S. sample – DEA 3-input/2-output model with common frontier

	(1) Bias-adjusted coefficients	95% bootstrap confidence intervals		(2) Bias-adjusted coefficients	95% bootstrap confidence intervals		(3) Bias-adjusted coefficients	95% bootstrap confidence intervals	
		low	high		high	low		high	low
GDP	-0.848***	-1.039	-0.677	-0.854***	-1.037	-0.685	-0.840***	-1.026	-0.671
NOFAC	-0.035***	-0.042	-0.027	-0.036***	-0.043	-0.028	-0.033***	-0.04	-0.025
MED	0.072*	-0.008	0.146	0.073*	-0.008	0.146	0.068*	-0.015	0.141
FOUND	-0.01	-0.059	0.043	-0.019	-0.071	0.036	-0.007	-0.058	0.045
TECH	0.126*	-0.005	0.247	0.123*	-0.008	0.243	0.130*	-0.001	0.25
REV_GOV				0.148	-0.08	0.377			
REV_FEE							0.288*	-0.005	0.551
	1672			1672			1672		

Notes: * indicates that the value zero does not fall within the 90% confidence interval, ** indicates that the value zero does not fall within the 95% confidence interval, *** indicates that the value zero does not fall within the 99% confidence interval. Confidence intervals obtained from 1000 bootstrapping interactions.
Constants are not reported. Year included in all models.
Source: own calculations

Figure 1

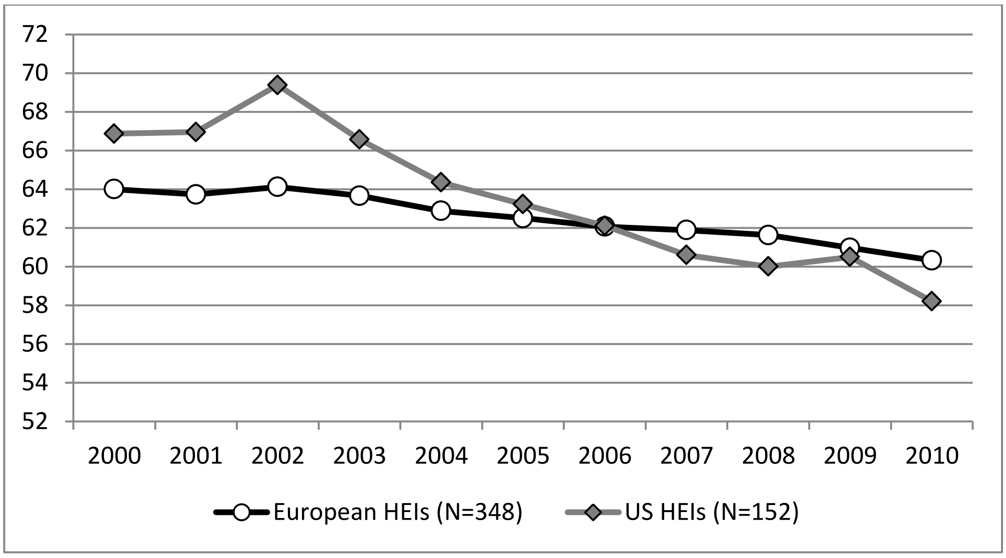
Revenue per student in real euros (2000-2010), European versus U.S. HEIs



Source: authors' elaboration

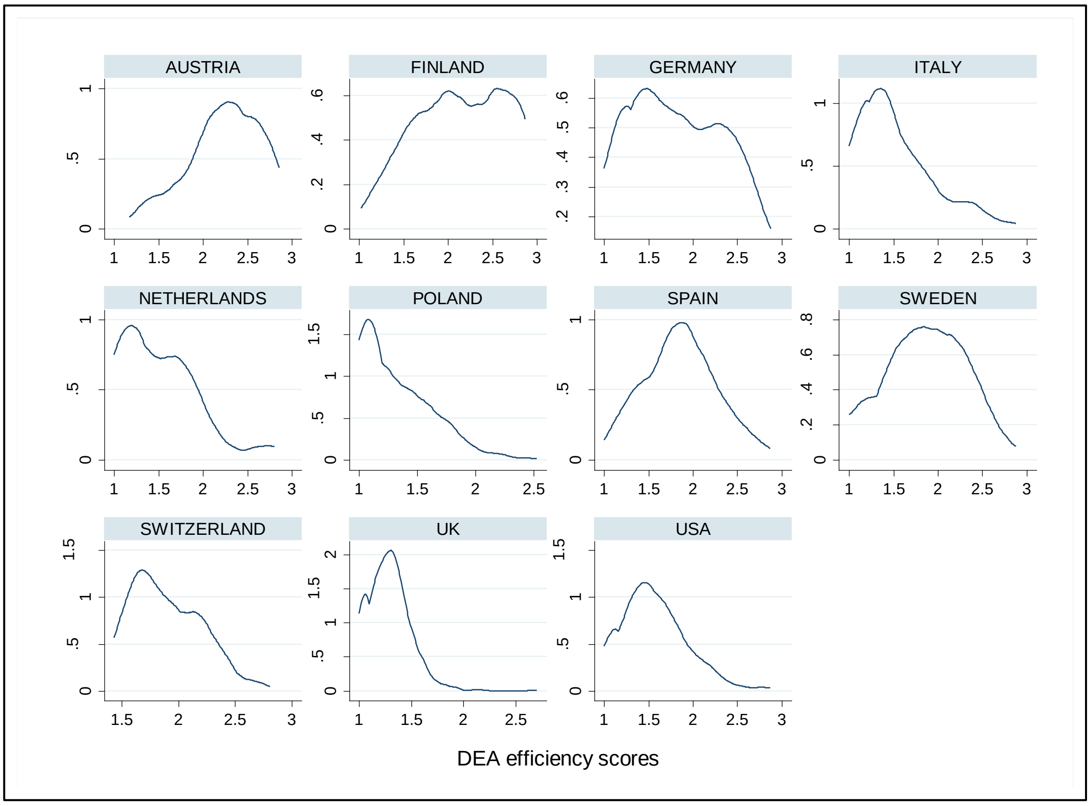
Figure 2

The share of revenue from government funding (2000-2010), European versus U.S. HEIs



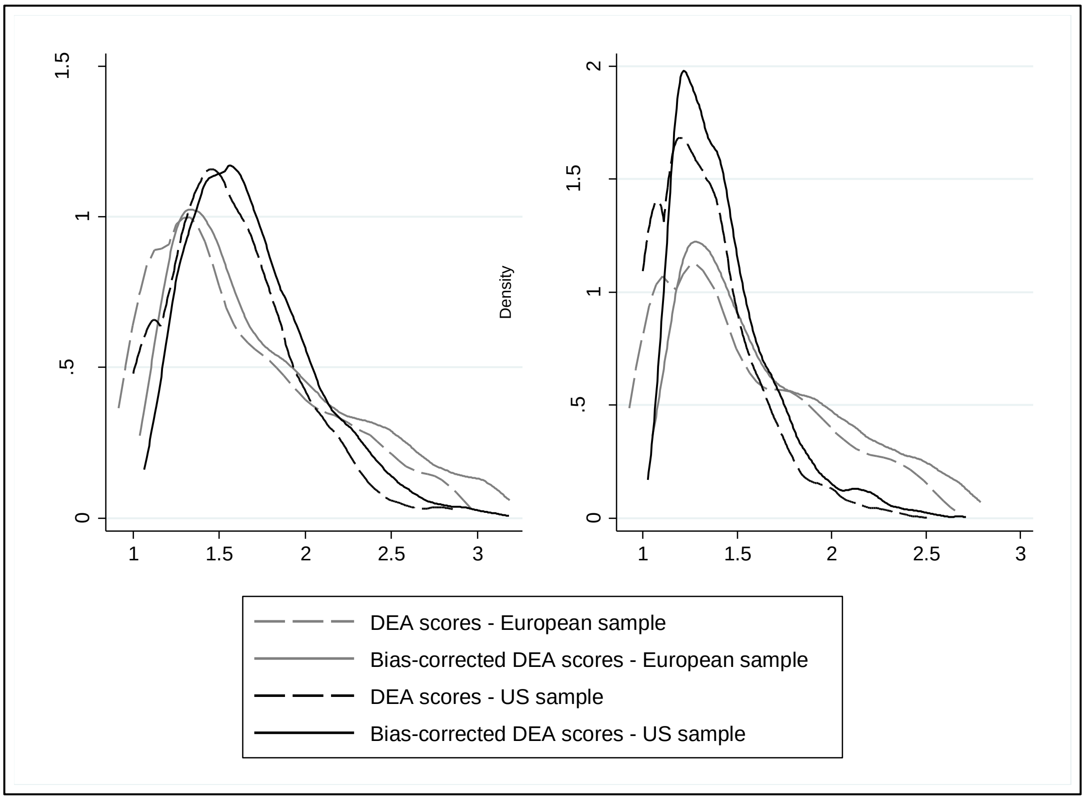
Source: authors' elaboration

Figure 3. The distribution of efficiency scores by country (all years pooled), common frontier.



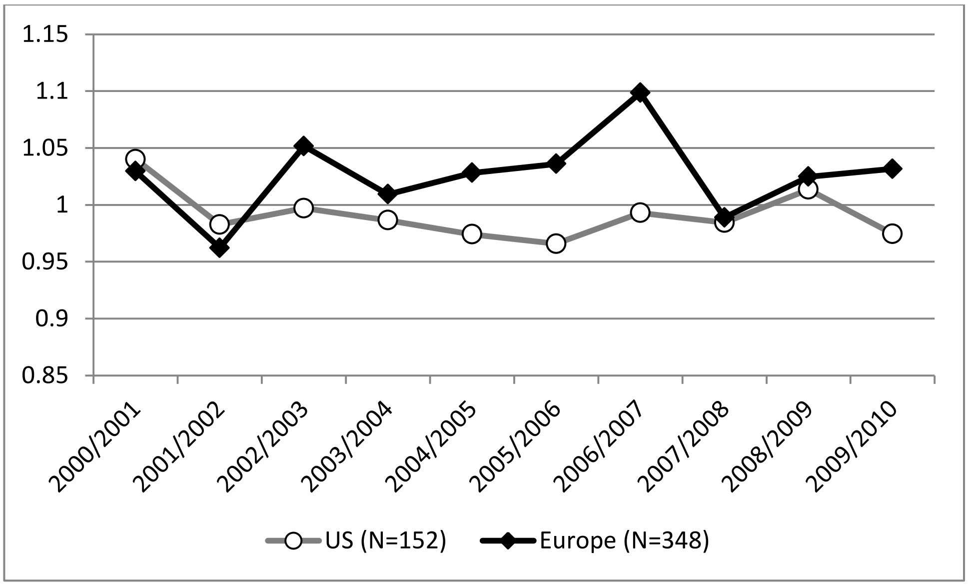
Source: Own elaboration

Figure 4. The distribution of DEA and bias-corrected DEA efficiency scores: global versus European-US frontier



Source: own elaboration

Figure 5. Annual changes in TFP (Malmquist indexes) in the period 2000-2010, U.S. and European sample



Notes: results based on Malmquist indexes that are statistically significant at 10% level. The results are based on DEA model 1: three inputs (expenditure, academic staff, students)/two outputs (publications, graduates); a common efficiency frontier is imposed.

Appendix

Table A1 Selective empirical studies using DEA to evaluate the efficiency of Higher Education in more than one country

No.	Author	Level of analysis, country and period coverage	Methodology	Inputs (I)/Outputs (O)	Main results
1	Agasisti (2011)	Higher education sectors in 18 OECD countries, 2000-2003 averages	DEA and FDH, CRS and VRS, input oriented, second stage analysis with the use of tobit regression	**I:** expenditure on tertiary education as a percentage of GDP, from public and private sources, net entry rates into tertiary education, ratio of students to teaching staff in tertiary education **O:** percentage of population completing tertiary education, percentage of tertiary graduates to the population at the typical age of graduation, employment rate, foreign student enrolments as a percentage of all students for total tertiary enrolment	UK and Swiss higher education systems are the most efficient. There is a positive correlation between GDP per capita of a given country and its higher education system efficiency only when other control variables are included. In some specifications the percentage of public funding for tertiary education is negatively correlated with its efficiency.
2	Agasisti and Johnes (2009)	57 Italian universities and 127 in the UK. 2002/2003 - 2004/2005	CRS, VRS, Malmquist index	**I:** total number of students, total amount of financial resources/income, number of PhD students, number of academic staff. **O:** number of graduates, total amount of external grants and contracts for research	Universities from the UK are more efficient but Italian ones are improving their technical efficiency while English universities obtain stable scores.
3	Agasisti and Pérez--Esparrells (2010)	57 Italian universities and 46 in Spain, 2000/2001 and 2004/2005	CRS, VRS, Malmquist index	**I:** total number of students, number of PhD students, total amount of financial resources, number of professors **O:** number of graduates, total amount of external grants and contracts for research	In the year 2000/2001 the efficiency of Italian and Spanish universities was similar. In 2004/2005 Italian universities were more efficient. An impact of regions on the efficiency scores confirmed.
4	Agasisti and Pohl (2012)	53 Italian universities and 69 in Germany, 2001 -2007	Output-oriented model, CRS, VRS, Malmquist index. Two-stage analysis through tobit model	**I:** total number of students, number of academic staff, expenditure **O:** number of graduates, total amount of external grants and contracts for research	German universities are more efficient, but Italian ones improved more rapidly. Universities in economically disadvantaged regions have gained efficiency over time. Universities with a medical faculty and operating in regions with a higher unemployment rate are less efficient while the regional share of employees working in science and technology is positively associated with efficiency.
5	Bonaccorsi et al. (2007a)	79 universities in 4 countries (Italy, Spain, Portugal and Switzerland) 2000/2001	Output-oriented model, FDH. Ratio of conditional to unconditional efficiency measures	**I:** number of academic staff, number of administration and technical staff **O:** number of graduates, number of publications	Economies of scale confirmed for the efficiency of education (up to a certain level measured by the number of persons employed); for research efficiency, evidence of decreasing economies of scale; the model for both education and research shows no relationship between

					the size of the individual unit and efficiency
6	Bonaccorsi et al. (2007b)	4 disciplines in Universities in Finland (18), Italy (53), Norway (4) and Switzerland (10). 2002.	Output-oriented model. Ratio of conditional to unconditional efficiency measures	**I:** number of academic staff **O:** number of graduates, number of publications	Level of analysis: 4 research fields: Engineering and Technology, Medical sciences, Natural Sciences, Social sciences and Humanities. A positive relationship between size of department and university size and efficiency (at the level of four disciplines).
7	Bonaccorsi et al. (2014)	400 universities in 14 European countries. 2008 or 2009	Nonparametric approach based on directional distance functions	I: number of non-academic staff, number of academic staff, personnel expenditure, non-personnel expenditure **O**: total degrees ISCED 5, total degrees ISCED 6, PUB Number of published papers, International collaboration, normalized impact, high quality publications, excellence rate	Size (economy of scale) and specialization (economy of scope) have a statistically significant impact both jointly and separately, showing an inverted u-shape effect on efficiency.
	Colbert et. al. (2000)	1st sample: 24 MBA programmes in USA 2nd sample: 10 US MBA programs and 3 foreign ones	VRS, output orientated	I: faculty to student ratio, average GMAT score of students in the programme, number of electives offered O: 2 variables describing student satisfaction, 2 describing students' employer satisfaction and both	In a cross-country comparison only one of 10 programmes is found to be inefficient.
8	Joumady and Ris (2005),	Graduates from 209 HEIs in eight European countries 1994/1995 graduates, based on postal survey carried in 1998	VRS, output oriented	**I:** Student entry characteristics, Study provision (1) e.g. teaching characteristics, Study provision (2): Provision of work placements, Importance of work experience in HE Institution O: Level of vocational competencies acquired, Level of generic competencies acquired, Vertical vocational competencies match, Vertical generic competencies match, Horizontal competencies match	The United Kingdom, The Netherlands and Austria have the highest efficiency scores. Dutch HE institutions are relatively efficient at producing competencies, and at preparing their graduates for the needs of the labour market, and a combination of both.
9	Parteka and Wolszczak-Derlacz (2013)	266 universities in seven European countries, 2001-2005	Output oriented, Malmquist index	I: academic staff, total revenue, number of students O: graduates, publication indexed in Web of Science.	The average annual increase in productivity with the assumption of a common frontier is 4%; the largest increases in productivity are for HEIs in Germany, Italy and Switzerland.
10	Reichmann and Sommersguter-Reichmann (2006)	118 university libraries in Australia, Austria, Canada, Germany, Switzerland and the United States.	VRS	I: book materials held, number FTE employees O: number of serial subscriptions, number of regular opening hours per week, number of book materials added, total number of circulations and renewals	34 efficient libraries (17 European, 17 non-European). On average, the non-European libraries perform better than the European ones. libraries. Different environments impact in that both managerial and environmental efficiency are higher in the group of non-European libraries.
11	St. Aubyn et al. (2009)	Higher education sectors in 28 countries1998–2005	CRS and VRS, output oriented, second stage analysis with the use of tobit regression	**I:** academic staff per capita, students per capita, expenditure on higher education as a percentage of GDP **O:** graduates per capita, ISI publication per capita.	The most efficient countries are: UK, the Netherlands, Ireland, Sweden, Finland and Denmark. A good quality secondary system, output-based funding rules, independent evaluation of institutions and staff policy autonomy are positively related to efficiency.
12	Wolszczak-	259 universities in	Output orientated	**I:** academic staff, total revenue, number of students	Large variation of efficiency scores both within and

	Derlacz and Parteka (2011)	seven European countries, 2001-2005	model, CRS, two-stage analysis based on bootstrap truncated regression	**O:** graduates, publications indexed in Web of Science.	between countries. More efficient universities have a higher number of different departments, a larger proportion of females among the academic staff, a smaller percentage of funds from primary sources (mostly from governments) and are older.

Source: own compilation

Table A2 Sources of data on individual HEIs

country	Number of HEIs	Data source
Austria	11	Austrian Federal Ministryof Science and Research http://www.bmwf.gv.at/ https://oravm13.noc-science.at/apex/f?p=103:36::::::
Finland	13	Finnish Ministry of Education 2000 – 2009: https://kotaplus.csc.fi/online/Haku.do Since 2010: http://vipunen.csc.fi/.
Germany	65	Federal Statistical Office (Destatis) www.destatis.de Detailed final results of individual statistics on higher education are regularly published as part of Fachserie (Subject-Matter Series) 11 "Bildung und Kultur" (Education and Culture) of the Federal Statistical Office
Italy	54	National Agency for the Evaluation of Universities (ANVUR)
Netherlands	10	Association of Universities Netherlands (VSNU). Financial data from each university's report downloaded from web page
Poland	30	Ministry of Science and Higher Education. Financial data from individual institution financial reports published in the Journal of Laws.
Spain	47	Spanish Rectors Conference (CRUE), www.crue.org
Sweden	24	Swedish Higher Education Authority http://www.uk-ambetet.se/statistikuppfoljning/statistikdatabasomhogskolan.4.782a298813a88dd0dad800011884.html
Switzerland	9	Swiss Federal Statistic Office: www.statistique.admin.ch
UK	85	Higher Education Statistics Agency http://www.heidi.ac.uk/
US	152	Integrated Postsecondary Education Data System (IPEDS) http://nces.ed.gov/ipeds/ run by the National Center for Education Statistics

Source: own compilation

Table A3 DEA model specifications

	Frontier	Inputs	Outputs
Model 1A	Common frontier (all HEIs pooled together)	Total revenue, Academic staff, Total students	Publications, graduates
Model 2A		Total revenue, Academic staff	Publications, graduates
Model 3A		Total revenue, Academic staff, Administration staff, Total students	Articles, publications other than articles, graduates
Model 1B	Regional frontier (European-US frontier)	Total revenue, Academic staff, Total students	Publications, graduates
Model 2B		Total revenue, Academic staff	Publications, graduates
Model 3B		Total revenue, Academic staff, Administration staff, Total students	Articles, publications other than articles, graduates

Table A4 Pairwise correlation between different DEA models (Pearson coefficient)

	DEA scores						DEA unbiased scores					
	Common frontier			European-US frontier			Common frontier			European-US frontier		
Model	1A	2A	3A	1B	2B	3B	1A	2A	3A	1B	2B	3B
1A	1											
2A	0.87	1.00										
3A	0.79	0.93	1.00									
1B	0.92	0.78	0.69	1.00								
2B	0.82	0.90	0.83	0.86	1.00							
3B	0.74	0.83	0.90	0.75	0.91	1.00						
1A	0.99	0.84	0.75	0.90	0.79	0.70	1.00					
2A	0.86	0.99	0.91	0.77	0.90	0.81	0.84	1.00				
3A	0.79	0.93	0.99	0.68	0.82	0.88	0.76	0.92	1.00			
1B	0.89	0.74	0.65	0.99	0.83	0.71	0.90	0.74	0.65	1.00		
2B	0.80	0.89	0.81	0.85	0.99	0.90	0.79	0.89	0.82	0.83	1.00	
3B	0.72	0.82	0.88	0.74	0.90	0.99	0.69	0.80	0.88	0.71	0.90	1.00

Note: all Pearson coefficients significant at 1% level

Table A5 Pairwise correlation between Malmquist indices based on different DEA models (Pearson coefficient)

	Malmquist indices						Malmquist unbiased indices					
	Common frontier			European-US frontier			Common frontier			European-US frontier		
Model	1A	2A	3A	1B	2B	3B	1A	2A	3A	1B	2B	3B
Model	1.00											
1A	0.70	1.00										
2A	0.88	0.64	1.00									
3A	0.95	0.65	0.85	1.00								
1B	0.66	0.94	0.61	0.67	1.00							
2B	0.83	0.58	0.95	0.88	0.61	1.00						
3B	0.98	0.69	0.84	0.90	0.65	0.77	1.00					
1A	0.70	0.99	0.63	0.65	0.91	0.57	0.71	1.00				
2A	0.88	0.64	0.98	0.84	0.61	0.90	0.87	0.64	1.00			
3A	0.93	0.64	0.82	0.98	0.66	0.85	0.91	0.65	0.83	1.00		
1B	0.66	0.91	0.60	0.67	0.99	0.60	0.65	0.91	0.60	0.67	1.00	
2B	0.84	0.58	0.92	0.89	0.61	0.98	0.81	0.58	0.91	0.89	0.61	1.00

Note: Malmquist unbiased indices obtained by bootstrap method following Simar and Wilson (1999). All Pearson coefficients significant at 1% level

Table A6 The determinants of inefficiency scores for European sample – DEA 3-input/2-output model with regional (European-US) frontier

	(1)	95% bootstrap	(2)	95% bootstrap	(3)	95% bootstrap

	Bias-adjusted coefficients	confidence intervals		Bias-adjusted coefficients	confidence intervals		Bias-adjusted coefficients	confidence intervals	
		low	high		high	low		high	low
GDP	-0.295***	-0.39	-0.185	-0.289***	-0.399	-0.17	-0.247***	-0.32	-0.173
NOFAC	-0.018***	-0.024	-0.011	-0.015***	-0.022	-0.007	0.002	-0.004	0.006
MED	-0.296***	-0.35	-0.242	-0.341***	-0.395	-0.278	-0.075***	-0.121	-0.023
FOUND	0.056***	0.043	0.07	0.067***	0.049	0.083	0.007	-0.003	0.016
TECH	0.383***	0.314	0.445	0.406***	0.337	0.474	0.227***	0.147	0.295
REV_GOV				0.405***	0.124	0.684			
REV_FEE							-0.691***	-1.002	-0.39
	3826			3088			1576		

Notes: * indicates that the value zero does not fall within the 90% confidence interval, ** indicates that the value zero does not fall within the 95% confidence interval, *** indicates that the value zero does not fall within the 99% confidence interval. Confidence intervals obtained from 1000 bootstrapping interactions.
Constants are not reported. Year and country dummies included in all models.
Source: own calculations

Table A7 The determinants of inefficiency scores for the U.S. sample - DEA 3-input/2-output model with regional (European-US) frontier

	(1) Bias-adjusted coefficients	95% bootstrap confidence intervals		(2) Bias-adjusted coefficients	95% bootstrap confidence intervals		(3) Bias-adjusted coefficients	95% bootstrap confidence intervals	
		low	high		high	low		high	low
GDP	-0.69***	-0.874	-0.518	-0.7***	-0.879	-0.529	-0.689***	-0.871	-0.516
NOFAC	-0.023***	-0.03	-0.016	-0.025***	-0.031	-0.017	-0.023***	-0.03	-0.015
MED	0.074*	-0.002	0.15	0.075*	-0.001	0.149	0.073*	-0.007	0.148
FOUND	-0.001	-0.05	0.052	-0.015	-0.068	0.039	0.000	-0.05	0.052
TECH	0.147*	0.014	0.261	0.141*	0.009	0.254	0.148*	0.016	0.263
REV_GOV				0.29	-0.065	0.508			
REV_FEE							0.063*	-0.025	0.316
	1672			1672			1672		

Notes: * indicates that the value zero does not fall within the 90% confidence interval, ** indicates that the value zero does not fall within the 95% confidence interval, *** indicates that the value zero does not fall within the 99% confidence interval. Confidence intervals obtained from 1000 bootstrapping interactions.
Constants are not reported. Year dummies included in all models.
Source: own calculations

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