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Super-Efficiency of Education Institutions: An Application to Economics Departments

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Super-Efficiency of Education Institutions: An Application to Economics Departments

Abstract

This paper investigates the efficiency of 188 economics departments around the world using data from RePEc. We go beyond the heavily used data envelopment analysis and utilize partial frontier analysis - specifically order-*α* and order-*m* - which addresses some of the drawbacks of the standard efficiency frontier analysis and allows for so-called super-efficient departments. We examine the particularities of these approaches and find that the super-efficient departments are not only the "usual suspects". Furthermore, standard output rankings are not well correlated with our estimated efficiency rankings, which themselves are rather similar.

JEL-Codes: I210, I230, D610.

Keywords: super-efficiency, economics departments, data envelopment analysis, order-*α*, order-*m*, free disposal hull, RePEc.

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1 Introduction

There exists plenty of literature that examines the efficiency of (higher) education institutions. Early examples are Lindsay (1982), Bessent, Bessent, Charnes, Cooper, and Thorogood (1983), Breu and Raab (1994), Dundar and Lewis (1995) and Ng and Li (2000). More recent studies include McMillan and Chan (2006), Johnes (2006a), Johnes (2006b), Agasisti and Johnes (2009) and Sellers-Rubio, Mas-Ruiz, and Casado-Díaz (2010). Worthington (2001), Rhaiem (2017) and Witte and López-Torres (2017) provide comprehensive surveys.

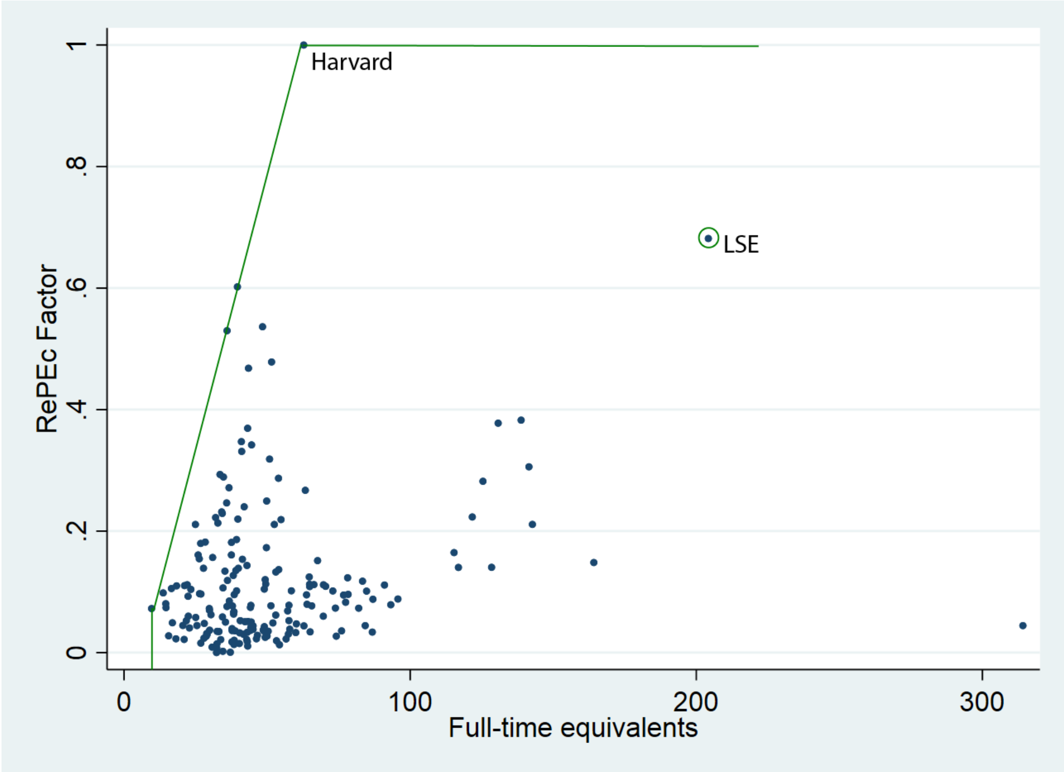
The lion's share of efficiency literature uses either data envelopment analysis (DEA)[1] or stochastic frontier analysis (SFA), although both methods have severe caveats that have been pointed out many times. The parametric SFA has been criticized for relying on restrictive assumptions concerning the functional form and the distribution of the error term. The non-parametric DEA suffers from being highly vulnerable to potential outliers and measurement error, because every unit is related to the most efficient units. This problem is illustrated in Figure 1, which depicts a cross-plot of the main factor of RePEc rankings as output variable on the vertical axis and full-time equivalents as input variable on the horizontal axis.[2] There is one obvious outlier (*Harvard University*) dominating the bulk of economics departments, making them inefficient in a DEA. Most (negatively) affected is the *London School of Economics* (LSE, red circle), which would be efficient if we leave out *Harvard University* and recalculate the efficiency hull. The problem is less severe, but remains if the free disposal hull (FDH) approach, which is less restrictive in defining the efficiency frontier, is used.

A simple idea to correct for potential outliers was proposed by Andersen and Petersen (1993). They propose to run the DEA leaving out one unit at a time. This potentially leads to super-efficient units with scores larger than one. A further improvement, partial frontier analysis (PFA), which rests upon the FDH approach, allows for a more general approach to investigating the efficiency of (higher) education institutions. The different PFA methods address the outlier-problem by generalizing FDH and allowing for super-efficient units, which lie beyond the estimated efficiency frontier. Two prominent examples of PFA are the order-m method by Cazals, Florens, and Simar (2002) and the order-α method by Aragon, Daouia, and Thomas-Agnan (2005). The former adds randomness to the FDH approach by calculating each efficiency score multiple times with a random subset of units, the latter utilizes only a certain percentile of comparison units when calculating each efficiency score.

This study makes four contributions to the literature. First, we add to the small literature using PFA with respect to education institutions. Bonaccorsi, Daraio, and Simar (2006) and Bonaccorsi, Daraio, Räty, and Simar (2007) apply an order-m approach to study 45 univer-

[1]Emrouznejad, Parker, and Tavares (2008) show how DEA has been used in scientific literature over time.
[2]The employed data set from RePEc is described in detail in section 3.

Figure 1: RePEc research output and full-time equivalents



sities in Italy and 261 universities across four European countries respectively. De Witte, Rogge, Cherchye, and Van Puyenbroeck (2013) use DEA as well as PFA to study the performance of 155 professors working at a Business & Administration department of a Brussels university college. Bruffaerts, Rock, and Dehon (2013) use FDH and PFA to study the efficiency of 124 U.S. universities. Finally, Bornmann and Wohlrabe (2018) study the super-efficiency of 50 U.S. universities with respect to top-cited papers. Secondly, we are the first to apply PFA to economics departments. So far, there are only few papers investigating their productivity or efficiency. Johnes (1988) uses self-created performance indicators to construct a ranking of the economics departments of 40 British universities. Johnes and Johnes (1992, 1993, 1995) conduct a DEA for 36 British and Madden, Savage, and Kemp (1997) for 24 Australian economics departments. Kocher, Luptácik, and Sutter (2006) compare country-level economic research efficiency using DEA. Conroy, Dusansky, and Kildegaard (1995), Cherchye and Abeele (2005) and Perianes-Rodríguez and Ruiz-Castillo (2014) employ other input-output measures not belonging to frontier efficiency class. Macri and Sinha (2006) provide an overview of international rankings, which are partly based on productivity considerations. This paper draws on Friedrich and Wohlrabe (2017) who conduct a DEA for 206 economics departments worldwide. Thirdly, we investigate whether there is a relationship between the RePEc ranking, which can be considered as a proxy for the reputation or influence of an economics department, and efficiency rankings. Fourthly, we are the first to compare five efficiency approaches in an empirical setup: DEA, the super-efficient DEA approach by Andersen and Petersen (1993) (SDEA), FDH, order-m and order-α. This allows us to take a differentiated look at efficiency measures. Krüger (2012) examines four of our approaches, but not SDEA, as well as parametric ones in a Monte Carlo study. He finds that SFA and standard DEA outperform the PFA methods in terms of mean-squared errors. Therefore, his recommendation, which we follow, is to cross-validate PFA results with other methods.[3] We mainly focus on ranking comparisons and want to know if the ordinal rankings differ across efficiency approaches.

For our analysis, we use a data set of 188 economics departments from RePEc. As only input variable we use full-time equivalents for authors affiliated with the respective department. Our output variables comprise the condensed information from 32 indicators, which represent both quantitative (scientific output, such as published work) and qualitative (scientific impact, such as number of citations) bibliometric information as well as readership (downloads and abstract views).

We proceed as follows. Section 2 explains the different approaches to measuring efficiency which we employ. Section 3 presents and describes our data. Section 4 contains the results of our efficiency analyses including some robustness checks. Section 5 draws conclusions from our findings.

2 Methodology

In this section, we outline the basic idea of the five approaches to efficiency measurement, which we employ. In all approaches we opt for output-orientation and assume variable returns to scale. We denote the input and output of department i with x_i and y_i, respectively. The efficiency score is denoted $\hat{e}_i$.

Being aware of the caveats discussed earlier, we begin with the simple non-parametric estimation of the educational efficiency frontier for later comparisons. We outline the standard data envelopment analysis (DEA) introduced by Charnes, Cooper, and Rhodes (1978). See Cooper, Seiford, and Zhu (2004) for a comprehensive discussion of DEA. We then state the basic idea of the super-efficient DEA approach by Andersen and Petersen (1993). Next, we explain the free disposal hull (FDH) approach which is somewhat less prone to outliers. The FDH approach was introduced by Deprins, Simar, and Tulkens (1984).

Both DEA and FDH are non-stochastic methods, as they assume all deviations from the frontier to be the result of inefficiencies. See Tauchmann (2012) for an illustrative example of both approaches. We continue by outlining the two partial frontier approaches, order-m and order-α. These techniques are generalizations of the FDH approach, which allow for super-efficient units, i.e. efficiency scores larger than one. Finally, we give a simple example to illustrate all five approaches.

[3] In this paper, we focus on non-parametric approaches and leave out parametric ones, such as SFA.

2.1 Data Envelopment Analysis

We illustrate the output-oriented approach with variable returns to scale which was proposed by Banker, Charnes, and Cooper (1984). The linear programming approach envelopes the data in a piecewise linear convex hull. The DEA efficiency score $\hat{e}_i^{DEA}$ solves the following optimization problem (Cordero-Ferrera, Pedraja-Chaparro, and Santín-González (2010)):

$$
\begin{aligned}
\max \quad & e^{DEA} + \epsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{i=1}^{s} s_r^+ \right) \text{ subject to} \\
& \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i0} \quad i = 1, 2, \ldots, m \\
& \sum_{j=1}^{n} \lambda_j y_{rj} - s_i^+ = e^{DEA} y_{r0} \quad i = 1, 2, \ldots, s \\
& \sum_{j=1}^{N} \lambda_j = 1 \quad j = 1, 2, \ldots, n \\
& s_i^- \geq 0; s_r^+ \geq 0 \qquad i = 1, 2, \ldots, m; \quad r = 1, 2, \ldots, s
\end{aligned}
$$

where i and r are the different inputs and outputs, λ is a weighting parameter that maximizes the productivity, s_i^+ and s_i^- are the input and output slacks, respectively, and ϵ is some small positive number. The efficiency score is given by $1/e^{DEA}$.

2.2 Super-efficient DEA

The approach by Andersen and Petersen (1993) builds upon the basic DEA by leaving out one department i at a time. A department is considered super-efficient, i.e. has an efficiency score larger than 1, if an department increase its input vector proportionally while preserving efficiency. The efficiency score reflects the radial distance from the department i under evaluation to the production frontier estimated with that one excluded from the sample, i.e. the maximum proportional increase in inputs preserving efficiency. This approach is especially useful when DEA delivers many efficient units, as it allows for a further differentiation by a more accurate ranking.

2.3 Free Disposal Hull

The FDH approach compares each department i with all other departments $j = 1, ..., N$ in the data set. The set of peer departments that satisfies the condition $y_{lj} \geq y_{li}$ $\forall l$ is denoted by B_i. Among the peer departments, the one that exhibits minimum input usage serves as reference to i and $\hat{e}_i^{FDH}$ is calculated as the relative input use

$$
\hat{e}_i^{FDH} = \min_{j \in B_i} \left\{ \max_{k=1,...K} \left(\frac{x_{kj}}{x_{ki}} \right) \right\}
$$

Departments that for a given output exhibit minimal input usage among all their peers serve as their own reference. For these units the efficiency score $\hat{e}_i^{FDH}$ is given by 1.

2.4 Order-m efficiency

In case of order-m efficiency, the partiality aspect comes in by departing from the assumption of benchmarking with the best-performing peer in the sample at hand. Instead, efficiency with respect to a sub-sample of m peers is considered. Daraio and Simar (2007) propose the following four-step procedure:

1. Draw from B_i a random sample of m peers (departments) with replacement.
2. A pseudo-FDH efficiency score ($\hat{e}_{mi}^{F\tilde{D}H_d}$) is calculated using the randomly drawn data.
3. Repeat steps 1 and 2 D times.
4. Order-m efficiency is calculated as the average of the pseudo-FDH scores:

$$\hat{e}_{mi}^{OM} = \frac{1}{D} \sum_{d=1}^{D} \hat{e}_{mi}^{\widetilde{FDH}_d}$$

A result of this procedure is that order-m efficiency scores may exceed the value of one. This is because in each replication d, department i may or may not serve as its own peer. As a consequence, there may be super-efficient departments ($\hat{e}_{mi}^{OM} > 1$) located beyond the estimated production possibility frontier. There are two parameters that need to be determined beforehand: m and D. The latter one is just a matter of accuracy. The higher D, the more clear-cut is the result, whether a department is super-efficient or not. Of course, a higher D increases the computation time. The choice of m is more critical. The smaller the value of m, the larger the share of super-efficient departments. For $m \to \infty$, the order-m approach converges to FDH, but for $m = N$ it is still possible that super-efficient departments occur.

2.5 Order-α efficiency

The order-α approach generalizes FDH in a different way. Instead of using the minimum input at a given output among available peers as a benchmark, order-α uses the αth percentile:

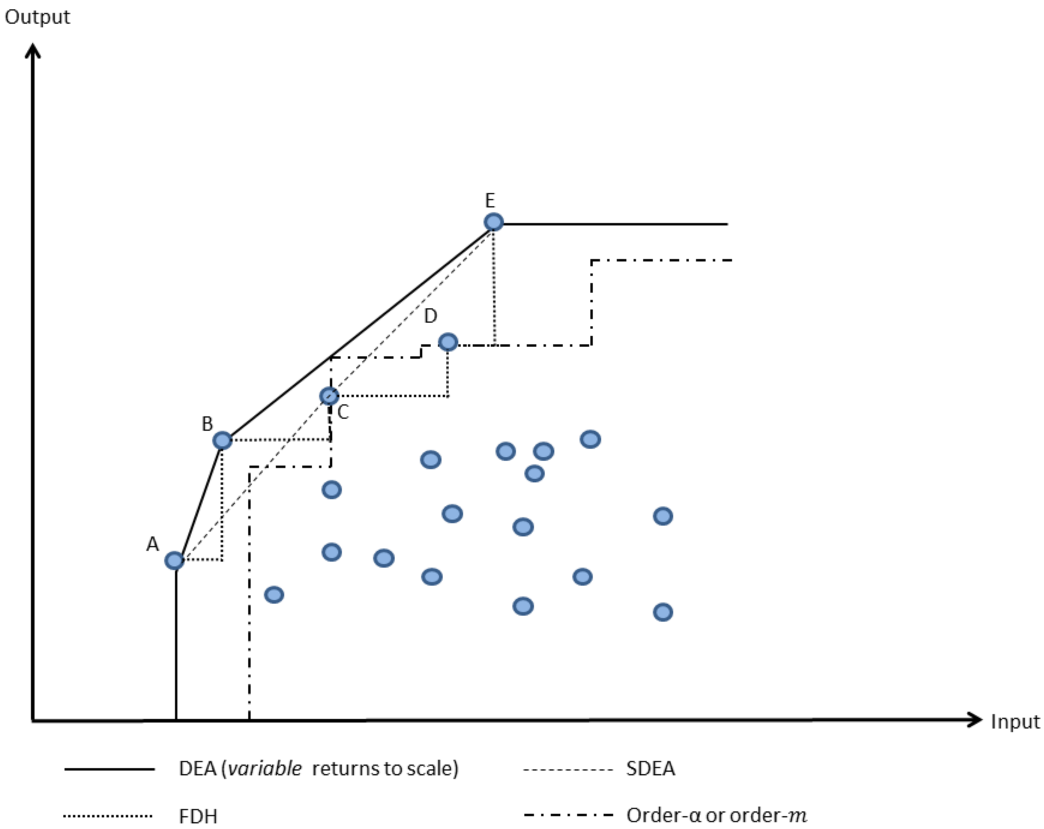
$$\hat{e}_{\alpha i}^{OA} = P_{j \in B_i}^{(\alpha)} \left\{ \max_{k=1,\dots K} \left(\frac{x_{kj}}{x_{ki}} \right) \right\}$$

When α=100, order-α reduces to FDH. In case $\alpha < 100$, some departments may be classified as super-efficient. Similar to m in the previous approach, α can be considered a tuning parameter: the smaller α the larger the share of super-efficient departments.

2.6 An illustrative example

In Figure 2, we display the outlined full and partial frontier analysis approaches in one graph. We plotted input-output combinations for various artificial departments. The DEA with variable returns to scale is given by the solid line. The educational production frontier is defined by the departments A, B and E. These three have an efficiency score of 1, i.e. an efficient input-output combination. All other departments to the right of or below the frontier are considered inefficient. Applying SDEA, we leave department B out and recalculate the efficiency curve. In turns out that C is now efficient and B potentially super-efficient. This depends on the resulting scores when all other departments are left out one at a time. In case of FDH, the outer hull is spanned more explicitly, by also considering points which are not on the DEA curve. In our example, departments C and D are now also efficient. The frontier has shifted to the right and efficiency scores for all other departments increase somewhat, as the distance to the frontier is smaller than for DEA. Applying the partial frontier approaches order-m or order-α, we get a different picture. Now, only departments C and D are just-efficient with a corresponding score of 1, whereas departments A, B and E are now super-efficient with a score larger than 1. Of course, both approaches do not necessarily yield the same results as Figure 2 would suggest.

Figure 2: An illustration of full and partial efficiency frontier analysis



Source: Own illustration.

3 Data

Our data is taken from the Research Papers in Economics (RePEc) website[4] and refers to February 2018. RePEc provides a large collection of bibliometric information and contains (meta) data both for bibliometric items (working papers, articles, chapters and books) and authors. Using gathered citations, RePEc calculates various impact measures for journals and working paper series. Those are the basis for ranking authors and economic institutions. RePEc has become quite a success, as of February 2018 there were 2.2 million pieces of research from 2,800 journals and 4,500 working paper series. Additionally, more than 50,000 authors and 14,000 institutions are listed on the website. For more details on RePEc see Zimmermann (2013).

We consider one input for any department: accumulated author shares. Each author sets a share by which he or she is affiliated with a department.[5] In case of no self-setting, RePEc calculates shares based on the other affiliated members of the institutions. In the following, we call these accumulated author shares full-time equivalents (FTE), as an institution with 10 authors, who all identify themselves with 80%, would have the same accumulated author share (or FTE) as an institution with 8 authors who all identify with 100%.

Using the information on bibliometric items and registered authors, RePEc currently (February 2018) provides 34 rankings for institutions, which could potentially serve as output indicators. Table 1 provides an overview of these measures. There are five main categories: number of (published) works, citations, citing authors, journal pages, and RePEc access statistics. Each of these main categories can be combined with different weighting schemes: simple or recursive impact factors, number of authors and combinations of them. In the category "distinct number of works" different versions of a paper are counted only once. Published work is counted only if, first the publisher provides the meta data to RePEc and second, the author assigns the work to his/her account. Table 1 reveals that there is a focus on citations both directly and indirectly. In 14 rankings, citations are counted with quality and time adjustments. Moreover, citations matter indirectly through the different impact factors. Zimmermann (2013) provides a detailed account of the methodology of RePEc.

We downloaded 32 publicly available rankings from the RePEc website, where the data refers to the January 2018 ranking.[6] For these rankings only the top 5% of world-wide institutions are shown. We selected all departments that were listed in all rankings. We excluded economic research institutions (e.g. ifo Institute), central banks and research networks (e.g.

[4]www.repec.org

[5]If author A identifies himself with 50% as an affiliate of institution A and with 50% of institution B, then both institutions increase their input by 0.5.

[6]We excluded two of the 34 available rankings: "Number of works" and "Strength of Students". The former due to the fact that it is always excluded in the ranking calculation in RePEc as it includes publications, mainly working papers, which are published several times in different series. The latter is based on a kind of genealogy in economics and is quite new. Some web research shows that it is currently rather incomplete.

NBER). Therefore, only economics departments remain, which makes the data homogeneous to a certain extent. Some units are sub-identities of larger organizational units, e.g. the *School of International and Public Affairs* and the *Finance and Economics Department* are both sub-units of *Columbia University*. We end up with a total of 188 units. A correlation analysis shows that the 32 rankings are highly correlated. 55% of all 496 bivariate correlations are larger than 0.9 and 75% larger than 0.8. This finding, which is in line with Seiler and Wohlrabe (2012) and Zimmermann (2013), indicates a high degree of similarity. In order to avoid an ad hoc choice we follow Seiler and Wohlrabe (2012) and define research performance as a latent process. Each of the 32 indicators can be regarded as an observed representation of this process. We run a principal component analysis (PCA) on our standardized data to extract the main components. This method has been used in the literature before to classify determinants of research productivity. See for instance Ramesh Babu and Singh (1998), Costas and Bordons (2007), Franceschet (2009), Docampo (2011), or Ortega, Lopez-Romero, and Fernandez (2011). Cordero-Ferrera, Pedraja-Chaparro, and Santín-González (2010) use PCA in a DEA framework to condense information. In our analysis, we extract two factors which serve as our outputs. The first one accounts for approximately 85% of the variation in the data, the second one for 9%. The remaining factors are negligible. In order to avoid counter-intuitive negative factor values, we rescale them to an interval from 0 to 1.

The nature of the data refers to the stock approach, i.e. a publication is assigned to the current affiliation of a researcher (partially in case of multiple affiliations). In contrast to this, one could adopt the flow approach where a work is credited to the institution that the author was affiliated with at the time of publication. Although the flow approach is preferable to the stock approach, it cannot be realized with RePEc data.

The RePEc data is consistent across departments for two reasons. First, authors can give weights to their affiliations (if they have more than one), which eliminates the need for arbitrary weighting that would have to be applied if an outsider performed this task. Second, RePEc enables authors to manage and verify their publication and citation list. In sum, the result is a largely consistent data set which allows for international comparisons.

4 Results

4.1 Basic Results

Following the methodology outlined in section 2, we estimate five efficiency scores for each economics department in our data set and obtain five efficiency rankings based on them. For later comparisons, we also calculate a RePEc ranking, which is based on the overall RePEc score from January 2018. The RePEc ranking can be considered as a proxy for the reputation of a department, because it measures *output* and *influence*, but not *efficiency*.

All efficiency score calculations use full-time equivalents as the single input and the two

Table 1: Bibliometric output measures in RePEc for institutions based on individual author scores.

		Without weighting	Simple Impact Factor	Recursive Impact Factor	Number of Authors	Number of Authors + Simple Impact Factor	Number of Authors + Recursive Impact Factor
Works	Overall	X					
	Distinct	X	X	X	X	X	X
Citations	Overall	X	X	X	X	X	X
	Discounted by citation year	X	X	X	X	X	X
Citing Authors	Overall	X					
	Weighted by authors rank	X					
Journal Pages		X	X	X	X	X	X
Access via RePEc	Abstract Views	X			X		
	Downloads	X			X		
Indices	h-Index	X					
	Euclidian Index	X					
Strength of Students		X					

extracted main factors as outputs. We assume output orientation with variable returns to scale. In Table 2 we provide some descriptive statistics for each approach plus the number of (super)-efficient departments. The average efficiency in case of DEA is 0.712 with a standard deviation of 0.12. For the other approaches the mean efficiency is higher, since the respective departments are shifted closer to the efficiency frontier. In addition, the standard deviation of the scores rises.

Table 3 displays the ten most efficient economics departments and their respective efficiency score for DEA, FDH, SDEA, order-α and order-m.[7] Panel 1 displays the results of the DEA. We find that 8 departments attain the efficiency frontier with the maximum efficiency score of 1. Among these are many of the "usual suspects"[8], such as *Harvard University*, *Yale University* or *Massachusetts Institute of Technology*. Panel 2 presents the results for the FDH approach. By construction, this approach finds more efficient departments than the DEA, which already found 8. In fact, we find 47 efficient departments, many of which are "usual suspects". Naturally, having 47 departments with the same efficiency rank (1) is rather unhelpful, which already foreshadows a key advantage of methods that allow for super-efficient departments. Panel 3 of Table 3 displays the results of the SDEA. We find 7 super-efficient departments, lead by *Harvard* with an efficiency score of 1.631, the *London School of Economics* (1.345) and the *Paris School of Economics* (1.120). At rank 8, *Yale* is

[7] A complete list of efficiency scores and ranks for all departments in alphabetical order can be found in Table 6 in the Appendix.

[8] Of course, we mean the term "usual suspects" in a very positive way. These are the institutions that would typically be expected at the top of these rankings, due to their excellent reputation.

the just-efficient department.

The previously employed methods - DEA, FDH, SDEA - do not require the specification of any parameters, making the efficiency score calculation straightforward. In contrast, PFA requires the specification of parameters, which eventually influence the amount of super-efficient departments. The order-α approach requires α, the percentile of the set of peer departments used as benchmark, and order-m m, the number of peer departments drawn randomly from the initial set of peer departments, being set ex ante. Figure 3 displays the number of super-efficient departments as functions of α and m, respectively. A similar exercise can be found in Cazals, Florens, and Simar (2002). Unless we set $m \rightarrow \infty$ or $\alpha = 100$, which is when the partial frontier approaches converge to FDH, we find super-efficient departments by construction. We set $\alpha = 99\%$ and $m = 130$ and get 15 (order-α) and 32 (order-m) super-efficient departments, respectively. The latter one is chosen because of some convergence of super-efficient departments at the value of 32 as m grows. The former is chosen to obtain a low number of super-efficient units. Setting α to 98%, we would have 44 super-efficient departments which we consider too many in our empirical application. Nevertheless, our calibration is somewhat arbitrary, but as we focus on the efficiency ranks and not the score, the number of super-efficient departments, and thus the calibration, has a limited impact.

Panel 4 presents the results obtained using the order-α PFA. The ranking is led by the *London School of Economics* with an efficiency score of 1.781, followed by *Harvard* (1.661) and *SciencesPo* (1.423). Notably, 17 departments are just-efficient using this approach. Panel 5 displays the results of the order-m PFA. Interestingly, the first nine departments are also among the first nine departments using the order-α PFA, while the exact ranking differs. The *London School of Economics* (1.270) still leads the ranking, but is now followed by the *Paris School of Economics* (1.255) and *Harvard* (1.214).

Looking at the five efficiency rankings from a broader perspective, it is noteworthy that next to the renowned U.S. universities, there is also a number of European universities appearing regularly. Among these are the *London School of Economics* (in the top ten of all 5 rankings), the *Paris School of Economics* (5), the *SciencesPo* (4), *Tilburg University* (3), *Oxford University* (3), *Barcelona GSE* (3), and *Bocconi University* (3). Among the super-efficient departments are also some not so well-known departments, like the *Crawford School of Public Policy* at the *Australian National University* and the economics department in *Groningen* (Netherlands).

Having so far only looked at the top-ranked departments, we now turn to a comparison of the complete rankings. Figure 4 displays scatter plots for all ranking combinations, including the RePEc ranking. Table 4 shows the corresponding rank correlation coefficients (Spearman's rho). Panel 2 (counting from left to right, top to bottom) shows that DEA and SDEA produce almost identical results, the rank correlation coefficient being 1.00. The SDEA additionally allows to discriminate among the efficient departments as found by the

DEA. The other scores remain the same for both approaches. The other panels show that the three super-efficient methods also produce similar results, the correlations being 0.966, 0.792 and 0.778. In contrast, the scatter plots comparing super-efficient methods with DEA or FDH look slightly more dispersed. Nevertheless, they are decently correlated with rank correlation coefficients above 0.75 throughout. Figure 4 also reveals that the PFA classifies many departments as just-efficient with a score of 1.000.

However, the most interesting result is displayed in Panels 11-15 (bottom row), which show that there is only a weak link between the RePEc ranking and the efficiency rankings. The PFA approaches are slightly higher correlated with the RePEc ranking, but the correlation never surpasses 0.612. The DEA and FDH rankings even have correlations of less than 0.4 with the RePEc ranking. We conclude that efficiency is not well correlated with reputation. Of course, in a strict sense, this low correlation should not be surprising, as RePEc and the efficiency scores effectively measure different things.

Figure 3: Number of super-efficient departments for different values of α and m

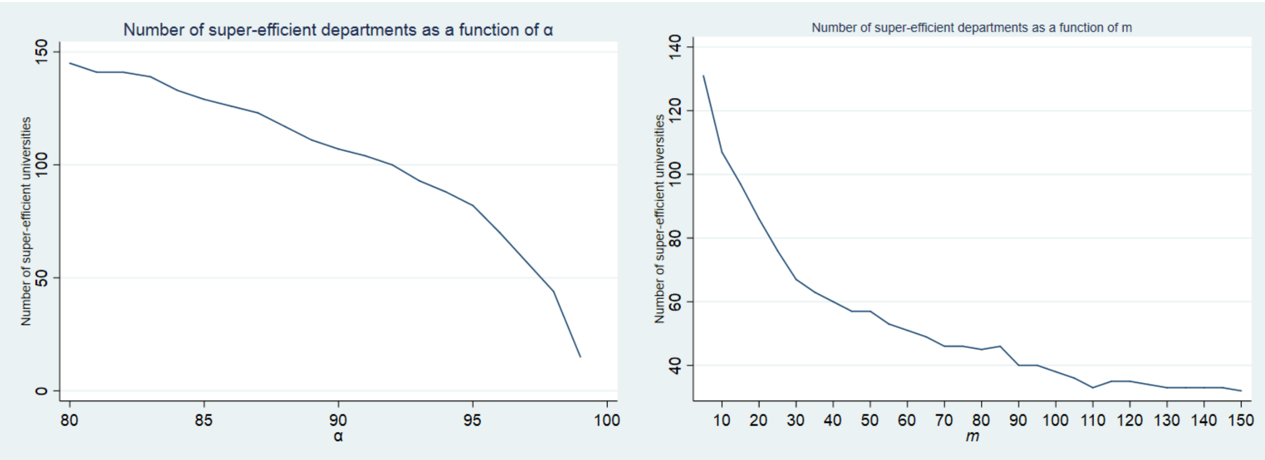


Table 2: Summary statistics of efficiency scores

	Mean	Standard Deviation	Minimum	Maximum	(Super-)efficient
DEA	0.712	0.120	0.471	1.000	8
FDH	0.851	0.122	0.543	1.000	47
SDEA	0.719	0.147	0.471	1.631	7
Order-α	0.899	0.171	0.584	1.781	15
Order-m	0.876	0.134	0.585	1.270	32

4.2 Robustness

In order to test whether the medium-sized correlation between the RePEc ranking and the efficiency rankings is robust, we modify all five approaches as follows:

Table 3: Top-ranked departments for each efficiency ranking

Rank	Institution	Score
	DEA	
1	London School of Econ. (LSE)	1.000
1	Paris School of Econ.	1.000
1	Depart. of Econ., Harvard U	1.000
1	Sciences economiques, Sciences Po	1.000
1	Depart. of Econ., U of California-Berkeley	1.000
1	Econ. Depart., Massachusetts Institute of Technology (MIT)	1.000
1	Charles H. Dyson School of Applied Econ. and Management, Cornell U	1.000
1	Cowles Foundation for Research in Econ., Yale U	1.000
9	Peter G. Peterson Institute for International Econ. (IIE)	0.996
10	Depart. of Econ., Princeton U	0.991
	FDH	
1	London School of Econ. (LSE)	1.000
1	Paris School of Econ.	1.000
1	School of Econ. and Management, Universiteit van Tilburg	1.000
1	Depart. of Econ., Oxford U	1.000
1	Depart. of Econ., Harvard U	1.000
1	Sciences economiques, Sciences Po	1.000
1	Crawford School of Public Policy, Australian National U	1.000
1	Universita Commerciale Luigi Bocconi	1.000
1	Barcelona Graduate School of Econ. (Barcelona GSE)	1.000
1	Depart. of Econ., U of California-Berkeley	1.000
	SDEA	
1	Depart. of Econ., Harvard U	1.631
2	London School of Econ. (LSE)	1.345
3	Paris School of Econ.	1.120
4	Sciences economiques, Sciences Po	1.092
5	Depart. of Econ., U of California-Berkeley	1.074
6	Charles H. Dyson School of Applied Econ. and Management, Cornell U	1.046
7	Econ. Depart., Massachusetts Institute of Technology (MIT)	1.042
8	Cowles Foundation for Research in Econ., Yale U	1.000
9	Peter G. Peterson Institute for International Econ. (IIE)	0.996
10	Depart. of Econ., Princeton U	0.991
	order-α	
1	London School of Econ. (LSE)	1.781
2	Depart. of Econ., Harvard U	1.661
3	Sciences economiques, Sciences Po	1.423
4	Depart. of Econ., U of California-Berkeley	1.413
5	Paris School of Econ.	1.412
6	Depart. of Econ., Oxford U	1.339
7	School of Econ. and Management, Universiteit van Tilburg	1.322
8	Barcelona Graduate School of Econ. (Barcelona GSE)	1.292
9	Universita Commerciale Luigi Bocconi	1.263
10	Depart. of Econ., Boston College	1.115
	order-m	
1	London School of Econ. (LSE)	1.270
2	Paris School of Econ.	1.255
3	Depart. of Econ., Harvard U	1.214
4	Depart. of Econ., Oxford U	1.192
5	Universita Commerciale Luigi Bocconi	1.144
6	School of Econ. and Management, Universiteit van Tilburg	1.141
7	Barcelona Graduate School of Econ. (Barcelona GSE)	1.135
8	Sciences economiques, Sciences Po	1.118
9	Depart. of Econ., U of California-Berkeley	1.082
10	Econ. Depart., Massachusetts Institute of Technology (MIT)	1.053

Figure 4: Cross-plots for all rankings

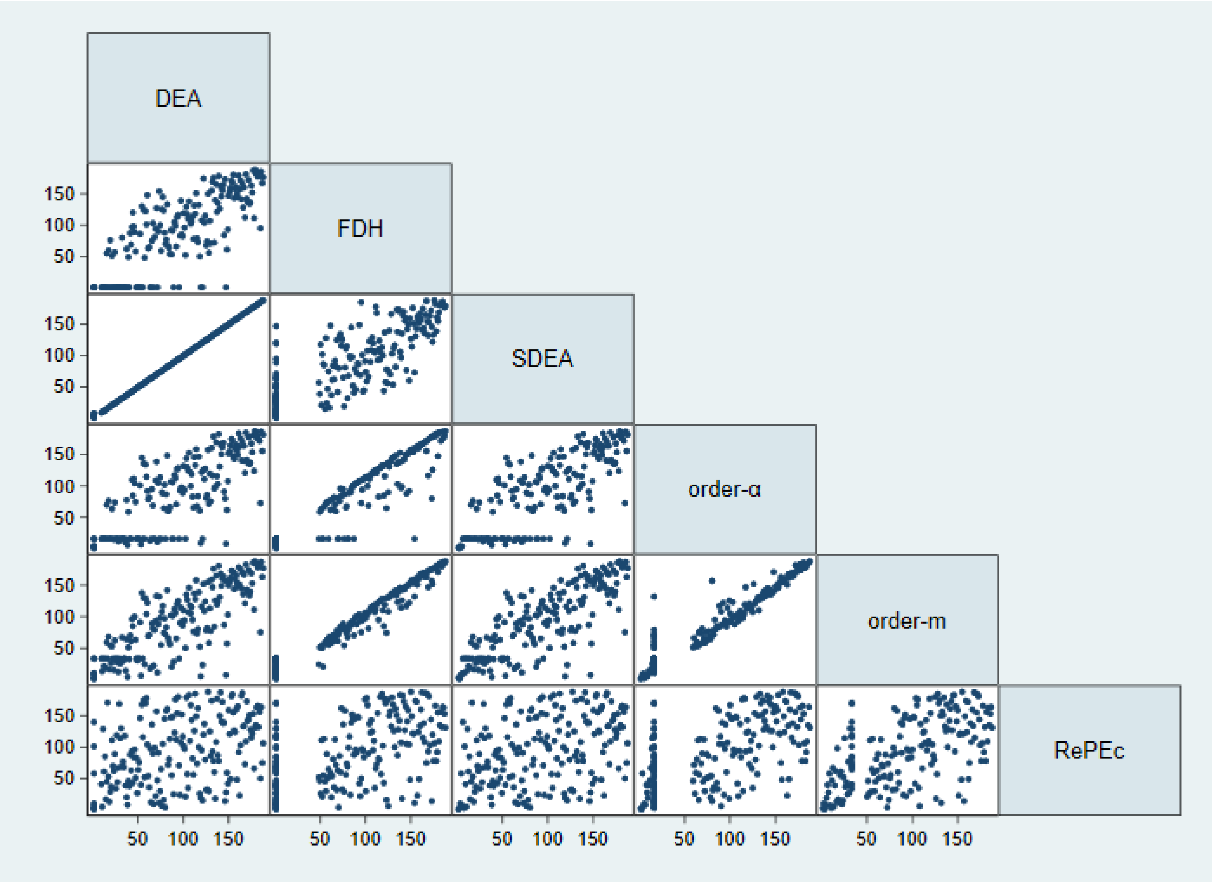


Table 4: Spearman rank correlation among efficiency ranks and the RePEc rank

	DEA	FDH	SDEA	order-α	order-m	RePEc
DEA	1.000					
FDH	0.788	1.000				
SDEA	1.000	0.788	1.000			
Order-α	0.778	0.925	0.778	1.000		
Order-m	0.791	0.977	0.792	0.966	1.000	
REPEC	0.386	0.517	0.387	0.612	0.599	1.000

1. We assume input orientation in contrast to output orientation.
2. Instead of two factors, all 32 RePEc rankings serve simultaneously as outputs.
3. The number of authors, in contrast to full-time equivalents, is used as the input.

In Table 5 we document the corresponding rank correlations with the overall RePEc ranking. The correlation is somewhat higher when input-orientation is used. This is also the case when all rankings serve as outputs. The reason for this might be a loss of information which is natural when information condensation approaches are applied. Unsurprisingly, using the coarser input measure of authors shrinks the correlation. However, the overall picture of a weak relationship between output and efficiency rankings remains.

Table 5: Spearman rank correlations with RePEc ranking for various changes to the efficiency approaches

	Input-oriented	All RePEc rankings as output	Authors as Input
DEA	0.510	0.737	0.278
FDH	0.601	0.645	0.570
SDEA	0.509	0.738	0.280
Order-α	0.572	0.694	0.663
Order-m	0.547	0.702	0.638

5 Conclusion

The results of our analysis allow for three conclusions. First, using the standard DEA and FDH approaches to measure efficiency, we find many well-known economics departments of renowned universities among the top ten, such as *Harvard University*, *Princeton University*, the *Massachusetts Institute of Technology* and *Yale University*. However, using the more robust order-α and order-m approaches, we also find smaller and less-known departments, such as of the *University of Groningen* and the *Crawford School of Public Policy* at the *Australian National University* atop the list. The reason for this difference is technical. In a DEA- or FDH-based efficiency measurement, departments, which have the highest output are automatically atop the list, as they receive the highest possible score of 1. Using methods, which allow for super-efficient units, smaller departments with mediocre output but also very small input can achieve an efficiency score larger than 1. We conclude that the well-known economics departments of renowned universities are not necessarily also the most efficient ones, as there might be some smaller departments, which make better use of their limited resources.

Secondly, based on Figure 4 and Table 4, we conclude that renowned departments are not necessarily efficient and efficient departments not necessarily renowned, as the correlation between any efficiency ranking and the RePEc ranking, which is used as a proxy for reputation, is rather small. This finding is consistent with Friedrich and Wohlrabe (2017) and holds for other choices of the parameters α and m.

Thirdly, we see from our comparison of five efficiency measures, that order-α and order-m produce very similar results. Both also produce similar results to FDH, on which they are based, for a small number of super-efficient units. In contrast, standard DEA produces to some extent different results, as Figure 4 displays. We conclude that a thorough efficiency analysis should feature multiple methods, as these diverge under certain circumstances. The lack of a dominant method suggests that there remains room for methodological advances and refinement of the applied measures.

There is a technical caveat to our analysis due to details of PFA, that deserves mentioning. It would seem natural to ask *whether there are* super-efficient economics departments before evaluating *which ones* are super-efficient, as we did in section 4. We motivated the existence of super-efficient departments with the mere look of the data in Figure 1. It is important to mention, that the former question cannot be answered using PFA, because the number of super-efficient departments depends crucially on our choice of the parameters α and m. Figure 3 visualizes this relationship. This issue is of limited significance for our analysis, because the parameters mainly affect the score, but not the ranking of departments. However, further studies might discuss this question in more detail.

References

Agasisti, T., and G. Johnes (2009): "Beyond frontiers: comparing the efficiency of higher education decision-making units across more than one country," *Education Economics*, 17(1), 59–79.

Andersen, P., and N. C. Petersen (1993): "A procedure for ranking efficient units in data envelopment analysis," *Management science*, 39(10), 1261–1264.

Aragon, Y., A. Daouia, and C. Thomas-Agnan (2005): "Nonparametric frontier estimation: a conditional quantile-based approach," *Econometric Theory*, 21(2), 358–389.

Banker, R. D., A. Charnes, and W. W. Cooper (1984): "Some models for estimating technical and scale inefficiencies in data envelopment analysis," *Management science*, 30(9), 1078–1092.

Bessent, A. M., E. W. Bessent, A. Charnes, W. W. Cooper, and N. C. Thorogood (1983): "Evaluation of educational program proposals by means of DEA," *Educational Administration Quarterly*, 19(2), 82–107.

Bonaccorsi, A., C. Daraio, T. Räty, and L. Simar (2007): "Efficiency and University Size: Discipline-wise Evidence from European Universities," MPRA Paper 10265, University Library of Munich, Germany.

Bonaccorsi, A., C. Daraio, and L. Simar (2006): "Advanced indicators of productivity of universitiesAn application of robust nonparametric methods to Italian data," *Scientometrics*, 66(2), 389–410.

Bornmann, L., and K. Wohlrabe (2018): "How efficiently produce elite US universities highly cited papers? A case study based on input and output data," Working paper, Ifo Munich, Germany.

Breu, T. M., and R. L. Raab (1994): "Efficiency and perceived quality of the nation's top 25 National Universities and National Liberal Arts Colleges: An application of data envelopment analysis to higher education," *Socio-Economic Planning Sciences*, 28(1), 33–45.

Bruffaerts, C., B. D. Rock, and C. Dehon (2013): "The Research Efficiency of US Universities: a Nonparametric Frontier Modelling Approach," Working Papers ECARES ECARES 2013-31, ULB – Universite Libre de Bruxelles.

Cazals, C., J.-P. Florens, and L. Simar (2002): "Nonparametric frontier estimation: a robust approach," *Journal of Econometrics*, 106(1), 1 – 25.

Charnes, A., W. W. Cooper, and E. Rhodes (1978): "Measuring the efficiency of decision making units," *European Journal of Operational Research*, 2(6), 429–444.

Cherchye, L., and P. V. Abeele (2005): "On research efficiency: A micro-analysis of Dutch university research in Economics and Business Management," *Research policy*, 34(4), 495–516.

Conroy, M. E., R. Dusansky, and A. Kildegaard (1995): "The productivity of economics departments in the US: Publications in the core journals," *Journal of Economic Literature*, 33(4), 1966–1971.

Cooper, W. W., L. M. Seiford, and J. Zhu (2004): *Data envelopment analysis*. Springer.

Cordero-Ferrera, J., F. Pedraja-Chaparro, and D. Santín-González (2010): "Enhancing the inclusion of non-discretionary inputs in DEA," *Journal of the Operational Research Society*, 61(4), 574–584.

Costas, R., and M. Bordons (2007): "The h-index: Advantages, limitations and its relation with other bibliometric indicators at the micro level," *Journal of Informetrics*, 1(3), 193–203.

Daraio, C., and L. Simar (2007): *Advanced Robust and nonparametric methods in efficiency analysis: methodology and applications*. Springer Science & Business Media.

De Witte, K., N. Rogge, L. Cherchye, and T. Van Puyenbroeck (2013): "Accounting for economies of scope in performance evaluations of university professors," *Journal of the Operational Research Society*, 64(11), 1595–1606.

Deprins, D., L. Simar, and H. Tulkens (1984): "Measuring labor-efficiency in post offices," in *The Performance of Public Enterprises: Concepts and Measurement*, ed. by M. Marchand, P. Pestieau, and H. Tulkens, pp. 243–267. Elsevier.

Docampo, D. (2011): "On using the Shanghai ranking to assess the research performance of university systems," *Scientometrics*, 86(1), 77–92.

Dundar, H., and D. R. Lewis (1995): "Departmental productivity in American universities: Economies of scale and scope," *Economics of Education review*, 14(2), 119–144.

Emrouznejad, A., B. R. Parker, and G. Tavares (2008): "Evaluation of research in efficiency and productivity: A survey and analysis of the first 30 years of scholarly literature in DEA," *Socio-economic planning sciences*, 42(3), 151–157.

Franceschet, M. (2009): "A cluster analysis of scholar and journal bibliometric indicators," *Journal of the American Society for Information Science and Technology*, 60(10), 1950–1964.

Friedrich, E., and K. Wohlrabe (2017): "The efficiency of economics departments reconsidered," *Economics Bulletin*, 37(3), 1602–1611.

Johnes, G. (1988): "Determinants of research output in economics departments in British universities," *Research Policy*, 17(3), 171–178.

Johnes, G., and J. Johnes (1992): "Apples and oranges: the aggregation problem in publications analysis," *Scientometrics*, 25(2), 353–365.

——— (1993): "Measuring the research performance of UK economics departments: an application of data envelopment analysis," *Oxford Economic Papers*, 45(2), 332–347.

——— (1995): "Research funding and performance in UK university departments of economics: a frontier analysis," *Economics of Education Review*, 14(3), 301–314.

Johnes, J. (2006a): "Data envelopment analysis and its application to the measurement of efficiency in higher education," *Economics of Education Review*, 25(3), 273–288.

——— (2006b): "Measuring teaching efficiency in higher education: An application of data envelopment analysis to economics graduates from UK Universities 1993," *European Journal of Operational Research*, 174(1), 443–456.

Kocher, M. G., M. Luptácik, and M. Sutter (2006): “Measuring productivity of research in economics: A cross-country study using DEA,” *Socio-Economic Planning Sciences*, (4), 314–332.

Krüger, J. J. (2012): “A Monte Carlo study of old and new frontier methods for efficiency measurement,” *European Journal of Operational Research*, 222(1), 137–148.

Lindsay, A. W. (1982): “Institutional performance in higher education: the efficiency dimension,” *Review of Educational Research*, 52(2), 175–199.

Macri, J., and D. Sinha (2006): “Rankings methodology for international comparisons of institutions and individuals: An application to economics in Australia and New Zealand,” *Journal of Economic Surveys*, 20(1), 111–156.

Madden, G., S. Savage, and S. Kemp (1997): “Measuring Public Sector Efficiency: A Study of Economics Departments at Australian Universities,” *Education Economics*, 5(2), 153–168.

McMillan, M. L., and W. H. Chan (2006): “University efficiency: A Comparison and consolidation of results from stochastic and non-stochastic methods,” *Education economics*, 14(1), 1–30.

Ng, Y. C., and S. K. Li (2000): “Measuring the Research Performance of Chinese Higher Education Institutions: An Application of Data Envelopment Analysis,” *Education Economics*, 8(2), 139–156.

Ortega, J., E. Lopez-Romero, and I. Fernandez (2011): “Multivariate approach to classify research institutes according to their outputs: The case of the CSIC’s institutes,” *Journal of Informetrics*, 5(3), 323–332.

Perianes-Rodríguez, A., and J. Ruiz-Castillo (2014): “Within- and between-department variability in individual productivity: the case of economics,” *Scientometrics*, 102(2), 1497–1520.

Ramesh Babu, A., and Y. Singh (1998): “Determinants of research productivity,” *Scientometrics*, 43(3), 309–329.

Rhaiem, M. (2017): “Measurement and determinants of academic research efficiency: a systematic review of the evidence,” *Scientometrics*, 110(2), 581–615.

Seiler, C., and K. Wohlrabe (2012): “Ranking economists on the basis of many indicators: An alternative approach using RePEc data,” *Journal of Informetrics*, 6(3), 389–402.

SELLERS-RUBIO, R., F. J. MAS-RUIZ, AND A. B. CASADO-DÍAZ (2010): “University Efficiency: Complementariness versus Trade-off between Teaching, Research and Administrative Activities,” *Higher Education Quarterly*, 64(4), 373–391.

TAUCHMANN, H. (2012): “Partial frontier efficiency analysis,” *Stata Journal*, 12(3), 461–478.

WITTE, K. D., AND L. LÓPEZ-TORRES (2017): “Efficiency in education: a review of literature and a way forward,” *Journal of the Operational Research Society*, 68(4), 339–363.

WORTHINGTON, A. C. (2001): “An empirical survey of frontier efficiency measurement techniques in education,” *Education economics*, 9(3), 245–268.

ZIMMERMANN, C. (2013): “Academic rankings with RePEc,” *Econometrics*, 1(3), 249–280.

Appendix

Table 6: Efficiency scores and corresponding ranks for all approaches and all economics departments

Institutions	DEA Score	DEA Rank	FDH Score	FDH Rank	SDEA Score	SDEA Rank	order-α Score	order-α Rank	order-m Score	order-m Rank	RePEc Rank
Aix-Marseille School of Econ. (AMSE)	0.686	100	0.806	119	0.686	100	0.807	132	0.836	110	89
Anderson Graduate School of Management, U of California-Los Angeles (UCLA)	0.804	40	1.000	1	0.804	40	1.000	16	1.001	32	149
Andrew Young School of Policy Studies, Georgia State U	0.699	92	0.924	66	0.699	92	0.961	71	0.945	65	97
Argyros School of Business and Econ., Chapman U	0.675	109	0.825	106	0.675	109	0.825	119	0.825	115	80
Barcelona Graduate School of Econ. (Barcelona GSE)	0.616	147	1.000	1	0.616	147	1.292	8	1.135	7	42
Booth School of Business, U of Chicago	0.712	80	0.891	70	0.712	80	1.000	16	0.925	72	109
Business School, Deakin U	0.603	155	0.645	180	0.603	155	0.777	148	0.699	171	34
Business School, Imperial College	0.623	143	0.727	156	0.623	143	0.727	162	0.730	161	46
Business School, U of Technology Sydney	0.540	181	0.571	186	0.540	181	0.688	177	0.624	184	8
Cass Business School, City U	0.645	129	0.825	107	0.645	129	0.825	120	0.828	113	60
CentER for Economic Research, School of Econ. and Management, Universiteit van Tilburg	0.719	75	0.944	59	0.719	75	1.000	16	0.976	55	114
Center for Operations Research and Econometrics (CORE), Ecole des Sciences Economiques de Louvain, Universite Catholique de Louvain	0.869	21	0.985	51	0.869	21	0.985	64	0.989	53	168
Center for Research in Econometric Analysis of Time Series (CREATES), Institut for Okonomi, Aarhus Universitet	0.590	166	0.790	128	0.590	166	0.790	140	0.790	136	23
Centre de Recherche en Economie et Statistique (CREST)	0.711	83	0.902	67	0.711	83	0.995	60	0.945	66	106
Centre for Economic Performance (CEP), London School of Econ. (LSE)	0.902	15	0.961	55	0.902	15	0.961	70	0.961	59	174
Centrum voor Economische StudiÃ«n, Faculteit Economie en Bedrijfswetenschappen, KU Leuven	0.708	86	0.856	92	0.708	86	0.856	107	0.858	102	103
Charles H. Dyson School of Applied Econ. and Management, Cornell U	1.000	1	1.000	1	1.046	6	1.000	16	1.000	33	183
College of Business and Econ., Australian National U	0.734	65	0.878	75	0.734	65	0.895	95	0.885	89	124
Copenhagen Business School	0.550	177	0.551	187	0.550	177	0.664	181	0.611	186	12
Cowles Foundation for Research in Econ., Yale U	1.000	1	1.000	1	1.000	8	1.000	16	1.000	33	181
Crawford School of Public Policy, Australian National U	0.861	23	1.000	1	0.861	23	1.000	15	1.034	15	166
Departament dEconomia i Empresa, Universitat Pompeu Fabra, Barcelona Graduate School of Econ. (Barcelona GSE)	0.547	178	0.818	111	0.547	178	0.820	124	0.833	111	11
Departament dEconomia i Historia Economica, Universitat Autonoma de Barcelona, Barcelona Graduate School of Econ. (Barcelona GSE)	0.641	131	0.730	155	0.641	131	0.730	161	0.735	159	58
Departamento de Economia, Universidad Carlos III de Madrid	0.603	156	0.757	143	0.603	156	0.787	143	0.771	144	33
Depart. of Agricultural and Resource Econ., U of California-Berkeley	0.984	11	1.000	1	0.984	11	1.000	16	1.000	33	178
Depart. of Econ. and Related Studies, U of York	0.632	138	0.769	135	0.632	138	0.859	103	0.817	123	51

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Table 6 – *cont. from previous page.*

	DEA		FDH		SDEA		order-α		order-m		RePEc
Institutions	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Rank
Depart. of Econ., Andrew Young School of Policy Studies, Georgia State U	0.688	99	0.872	82	0.688	99	0.906	89	0.888	86	90
Depart. of Econ., Boston College	0.815	36	1.000	1	0.815	36	1.115	10	1.034	14	153
Depart. of Econ., Boston U	0.691	96	0.868	83	0.691	96	0.899	93	0.883	90	93
Depart. of Econ., Cornell U	0.883	17	0.940	60	0.883	17	0.940	77	0.940	68	172
Depart. of Econ., Duke U	0.607	152	0.717	159	0.607	152	0.717	165	0.727	162	37
Depart. of Econ., Faculty of Business and Econ., U of Melbourne	0.699	91	0.841	99	0.699	91	0.841	113	0.844	106	98
Depart. of Econ., George Washington U	0.603	157	0.723	158	0.603	157	0.737	160	0.732	160	32
Depart. of Econ., Harvard U	1.000	1	1.000	1	1.631	1	1.661	2	1.214	3	188
Depart. of Econ., Hebrew U of Jerusalem	0.666	117	0.779	132	0.666	117	0.779	147	0.780	139	72
Depart. of Econ., Indiana U	0.699	90	0.829	105	0.699	90	0.829	118	0.829	112	99
Depart. of Econ., Iowa State U	0.839	31	1.000	1	0.839	31	1.000	16	1.002	31	158
Depart. of Econ., Johns Hopkins U	0.857	24	0.952	57	0.857	24	0.952	74	0.952	62	165
Depart. of Econ., Leicester U	0.650	127	0.744	150	0.650	127	0.744	158	0.748	155	62
Depart. of Econ., Management School, Lancaster U	0.669	113	0.806	118	0.669	113	0.806	133	0.809	128	76
Depart. of Econ., McGill U	0.726	70	0.793	127	0.726	70	0.793	139	0.795	133	119
Depart. of Econ., McMaster U	0.612	150	0.753	147	0.612	150	0.767	152	0.758	150	39
Depart. of Econ., Monash Business School, Monash U	0.833	32	0.873	80	0.833	32	1.000	16	0.940	67	157
Depart. of Econ., National U of Singapore (NUS)	0.599	158	0.709	161	0.599	158	0.709	166	0.717	166	31
Depart. of Econ., New York U (NYU)	0.735	64	1.000	1	0.735	64	1.000	16	1.022	19	125
Depart. of Econ., Northwestern U	0.649	128	0.959	56	0.649	128	0.959	72	0.962	58	61
Depart. of Econ., Ohio State U	0.660	120	0.821	108	0.660	120	0.821	122	0.823	116	69
Depart. of Econ., Oxford U	0.808	38	1.000	1	0.808	38	1.339	6	1.192	4	151
Depart. of Econ., Pennsylvania State U	0.631	139	0.651	178	0.631	139	0.651	183	0.651	181	50
Depart. of Econ., Princeton U	0.991	10	1.000	1	0.991	10	1.000	16	1.035	13	179
Depart. of Econ., Rutgers U-New Brunswick	0.786	43	0.845	97	0.786	43	0.845	110	0.864	96	146
Depart. of Econ., School of Arts and Sciences, Columbia U	0.720	73	0.731	154	0.720	73	1.000	16	0.796	132	116
Depart. of Econ., School of Business, Management and Econ., U of Sussex	0.688	98	0.867	85	0.688	98	0.883	98	0.873	92	91
Depart. of Econ., Sciences economiques, Sciences Po	0.754	55	1.000	1	0.754	55	1.000	16	1.000	33	134
Depart. of Econ., Simon Fraser U	0.671	112	0.783	131	0.671	112	0.783	146	0.790	137	77
Depart. of Econ., Stanford U	0.730	67	1.000	1	0.730	67	1.000	16	1.018	22	122
Depart. of Econ., Texas A&M U	0.668	114	0.738	151	0.668	114	0.738	159	0.739	158	75
Depart. of Econ., U College London (UCL)	0.653	125	0.896	68	0.653	125	0.929	81	0.913	78	64
Depart. of Econ., U of Birmingham	0.682	106	0.764	138	0.682	106	0.764	153	0.765	146	83
Depart. of Econ., U of Calgary	0.684	103	0.785	129	0.684	103	0.785	144	0.790	135	86

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Table 6 – *cont. from previous page.*

	DEA		FDH		SDEA		order-α		order-m		RePEc
Institutions	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Rank
Depart. of Econ., U of California-Berkeley	1.000	1	1.000	1	1.074	5	1.413	4	1.082	9	184
Depart. of Econ., U of California-Irvine	0.832	33	1.000	1	0.832	33	1.000	16	1.004	29	156
Depart. of Econ., U of California-Los Angeles (UCLA)	0.682	105	0.818	110	0.682	105	0.818	125	0.844	107	84
Depart. of Econ., U of California-San Diego (UCSD)	0.594	162	0.725	157	0.594	162	0.725	163	0.758	151	27
Depart. of Econ., U of California-Santa Barbara (UCSB)	0.773	48	1.000	1	0.773	48	1.000	16	1.000	33	141
Depart. of Econ., U of Chicago	0.717	76	0.795	125	0.717	76	0.903	90	0.841	108	113
Depart. of Econ., U of Colorado	0.682	107	0.820	109	0.682	107	0.820	123	0.821	118	82
Depart. of Econ., U of Connecticut	0.695	94	0.809	116	0.695	94	0.809	129	0.815	125	95
Depart. of Econ., U of Maryland	0.684	104	0.809	117	0.684	104	0.809	130	0.812	127	85
Depart. of Econ., U of Minnesota	0.639	133	0.671	175	0.639	133	0.671	179	0.671	176	56
Depart. of Econ., U of Notre Dame	0.555	175	0.702	163	0.555	175	0.702	168	0.706	169	14
Depart. of Econ., U of Pennsylvania	0.772	49	1.000	1	0.772	49	1.000	16	1.003	30	140
Depart. of Econ., U of Pittsburgh	0.540	180	0.618	182	0.540	180	0.618	186	0.620	185	9
Depart. of Econ., U of Southern California	0.852	27	1.000	1	0.852	27	1.000	16	1.009	27	162
Depart. of Econ., U of Texas-Austin	0.577	169	0.633	181	0.577	169	0.633	185	0.647	183	20
Depart. of Econ., U of Toronto	0.675	111	0.876	78	0.675	111	0.977	66	0.916	76	78
Depart. of Econ., U of Virginia	0.594	161	0.647	179	0.594	161	0.647	184	0.660	179	28
Depart. of Econ., U of Warwick	0.722	71	1.000	1	0.722	71	1.087	11	1.051	11	118
Depart. of Econ., U of Washington	0.818	35	1.000	1	0.818	35	1.000	16	1.000	33	154
Depart. of Econ., U of Western Ontario	0.775	45	0.843	98	0.775	45	0.843	112	0.862	99	144
Depart. of Econ., Vanderbilt U	0.954	12	1.000	1	0.954	12	1.000	16	1.019	21	177
Depart. of Econ., W.P. Carey School of Business, Arizona State U	0.655	124	0.812	115	0.655	124	0.812	128	0.816	124	65
Depart. of Econ., Washington U in St. Louis	0.708	85	0.974	54	0.708	85	0.974	67	0.974	56	104
Depart. of Geography and Environment, London School of Econ. (LSE)	0.900	16	1.000	1	0.900	16	1.000	16	1.000	33	173
Depart. Volkswirtschaftlehre, Universität Bern	0.747	58	0.805	122	0.747	58	0.805	134	0.806	129	131
Dipartimento di Economia e Finanza, Facolta di Economia, Universita degli Studi di Roma "Tor Vergata"	0.712	81	0.878	77	0.712	81	0.912	87	0.891	83	108
Dipartimento di Economia e Statistica "Cognetti de Martiis", Universita degli Studi di Torino	0.744	59	0.839	101	0.744	59	0.839	115	0.850	104	130
Dipartimento di Economia, Universita Ca Foscari Venezia	0.591	164	0.760	141	0.591	164	0.790	141	0.771	145	25
Dipartimento di Scienze Economiche "Marco Fanno", Universita degli Studi di Padova	0.627	141	0.702	162	0.627	141	0.702	167	0.712	168	48
Dipartimento di Scienze Economiche, Alma Mater Studiorum - Universita di Bologna	0.721	72	0.858	90	0.721	72	0.858	105	0.885	88	117

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Table 6 – *cont. from previous page.*

	DEA		FDH		SDEA		order-α		order-m		RePEc
Institutions	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Rank
Ecole des Sciences Economiques de Louvain, Universite Catholique de Louvain	0.796	42	0.896	69	0.796	42	1.000	16	0.955	61	147
Econ. Depart., Brown U	0.638	135	0.763	140	0.638	135	0.867	99	0.814	126	54
Econ. Depart., Dartmouth College	0.664	118	0.989	50	0.664	118	0.989	61	0.990	52	71
Econ. Depart., Georgetown U	0.774	47	0.947	58	0.774	47	0.947	75	0.950	63	142
Econ. Depart., London School of Econ. (LSE)	0.720	74	0.840	100	0.720	74	0.840	114	0.862	98	115
Econ. Depart., Massachusetts Institute of Technology (MIT)	1.000	1	1.000	1	1.042	7	1.000	16	1.053	10	182
Econ. Depart., Michigan State U	0.742	61	0.938	63	0.742	61	0.938	79	0.939	69	128
Econ. Depart., Organisation de Cooperation et de Developpement Economiques (OCDE)	0.620	145	0.868	84	0.620	145	0.902	91	0.886	87	44
Econ. Depart., Queens U	0.845	28	1.000	1	0.845	28	1.059	12	1.037	12	161
Econ. Depart., Stern School of Business, New York U (NYU)	0.693	95	1.000	1	0.693	95	1.000	16	1.000	33	94
Econ. Depart., U of California-Davis	0.805	39	0.996	49	0.805	39	0.996	59	0.997	51	150
Econ. Depart., U of California-Santa Cruz (UCSC)	0.853	26	1.000	1	0.853	26	1.000	16	1.000	33	163
Econ. Depart., U of Essex	0.624	142	0.754	146	0.624	142	0.769	151	0.760	149	47
Econ. Depart., U of Michigan	0.652	126	0.881	74	0.652	126	0.913	86	0.898	82	63
Econ. Depart., U of Missouri	0.760	54	0.783	130	0.760	54	0.783	145	0.783	138	135
Econ. Depart., U of Wisconsin-Madison	0.741	62	0.927	65	0.741	62	0.927	82	0.927	71	127
Econ. Depart., Yale U	0.947	14	1.000	1	0.947	14	1.000	16	1.025	18	175
Eitan Berglas School of Econ., Tel Aviv U	0.862	22	1.000	1	0.862	22	1.000	16	1.000	33	167
Ekonomihögskolan, Lunds Universitet	0.528	184	0.599	183	0.528	184	0.696	172	0.650	182	5
European Centre for Advanced Research in Econ. and Statistics (ECARES), Solvay Brussels School of Econ. and Management, Universite Libre de Bruxelles	0.686	101	0.845	96	0.686	101	0.895	94	0.870	94	88
Fachbereich Wirtschaftswissenschaft, Goethe Universität Frankfurt am Main	0.562	174	0.766	136	0.562	174	0.796	137	0.779	140	15
Fachbereich Wirtschaftswissenschaften, Universität Konstanz	0.490	186	0.588	185	0.490	186	0.588	187	0.590	187	3
Facultad de Economia y Negocios, Universidad de Chile	0.678	108	0.833	102	0.678	108	0.866	100	0.846	105	81
Faculte des Hautes Etudes Commerciales (HEC), Universite de Lausanne	0.588	167	0.710	160	0.588	167	0.724	164	0.717	167	22
Faculteit der Economische Wetenschappen, Erasmus Universiteit Rotterdam	0.641	132	0.691	169	0.641	132	0.832	117	0.764	147	57
Faculteit Economie en Bedrijfskunde, Rijksuniversiteit Groningen	0.736	63	1.000	1	0.736	63	1.040	13	1.031	17	126
Faculteit Economie en Bedrijfskunde, Universiteit van Amsterdam	0.642	130	0.889	71	0.642	130	0.942	76	0.916	77	59
Faculteit Economie en Bedrijfswetenschappen, KU Leuven	0.675	110	0.813	114	0.675	110	0.925	83	0.870	95	79
Faculty of Business and Econ., U of Melbourne	0.730	66	0.831	103	0.730	66	0.965	69	0.899	81	123

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Table 6 – *cont. from previous page.*

Institutions	DEA Score	DEA Rank	FDH Score	FDH Rank	SDEA Score	SDEA Rank	order-α Score	order-α Rank	order-m Score	order-m Rank	RePEc Rank
Faculty of Econ., U of Cambridge	0.750	57	0.997	48	0.750	57	1.000	16	1.014	24	132
Faculty of Econ., U of Tokyo	0.712	79	0.861	88	0.712	79	0.861	102	0.863	97	110
Fakultät für Wirtschaftswissenschaften, Universität Wien	0.657	123	0.829	104	0.657	123	0.845	111	0.838	109	66
Finance and Econ. Depart., Graduate School of Business, Columbia U	0.856	25	1.000	1	0.856	25	1.000	16	1.000	33	164
Graduate School of Business, Columbia U	0.728	69	0.852	94	0.728	69	0.852	109	0.871	93	120
Graduate School of Business, Stanford U	0.660	121	1.000	1	0.660	121	1.000	16	1.017	23	68
Groupement de Recherche en Economie Quantitative dAix-Marseille (GREQAM), Aix-Marseille School of Econ. (AMSE)	0.690	97	0.763	139	0.690	97	0.887	97	0.828	114	92
Handelshögskolan i Stockholm	0.586	168	0.817	112	0.586	168	0.821	121	0.819	121	21
Handelshögskolan, Göteborgs Universitet	0.569	173	0.775	134	0.569	173	0.805	135	0.791	134	16
Harris School of Public Policy, U of Chicago	0.774	46	0.859	89	0.774	46	0.859	104	0.859	100	143
Harvard Business School, Harvard U	0.614	149	0.853	93	0.614	149	0.853	108	0.854	103	40
Innocenzo Gasparini Institute for Economic Research (IGIER), Universita Commerciale Luigi Bocconi	0.770	50	1.000	1	0.770	50	1.000	16	1.000	33	139
Institut dEconomie Industrielle (IDEI), Toulouse School of Econ. (TSE)	0.819	34	1.000	1	0.819	34	1.000	16	1.000	33	155
Institut for Okonomi, Aarhus Universitet	0.614	148	0.939	61	0.614	148	0.989	62	0.967	57	41
Institut für Volkswirtschaftslehre, Wirtschaftswissenschaftliche Fakutät, Universität Zürich	0.479	187	0.695	167	0.479	187	0.755	156	0.726	163	2
Institutet för Näringslivsforskning (IFN)	0.631	140	0.794	126	0.631	140	0.809	131	0.799	131	49
International Food Policy Research Institute (IFPRI)	0.784	44	0.806	120	0.784	44	0.918	85	0.890	85	145
Kellogg Graduate School of Management, Northwestern U	0.598	159	0.745	149	0.598	159	0.745	157	0.748	154	30
Kennedy School of Government, Harvard U	0.881	18	1.000	1	0.881	18	1.000	16	1.032	16	171
London Business School (LBS)	0.593	163	0.688	171	0.593	163	0.688	176	0.689	175	26
London School of Econ. (LSE)	1.000	1	1.000	1	1.345	2	1.781	1	1.270	1	187
Management School, Lancaster U	0.633	137	0.805	121	0.633	137	0.837	116	0.820	119	52
Monash Business School, Monash U	0.874	19	0.878	76	0.874	19	1.000	16	0.977	54	170
National Graduate Institute for Policy Studies (GRIPS)	0.591	165	0.697	166	0.591	165	0.697	171	0.702	170	24
National Research U Higher School of Econ.	0.543	179	0.543	188	0.543	179	0.584	188	0.585	188	10
Nationalekonomiska Institutionen, Ekonomihögskolan, Lunds Universitet	0.576	170	0.758	142	0.576	170	0.788	142	0.773	143	19
Nationalekonomiska institutionen, Handelshögskolan, Göteborgs Universitet	0.597	160	0.756	144	0.597	160	0.770	150	0.761	148	29
Nationalekonomiska Institutionen, Uppsala Universitet	0.535	182	0.655	177	0.535	182	0.668	180	0.660	178	7
Norges HandelshOyskole (NHH)	0.532	183	0.596	184	0.532	183	0.692	174	0.654	180	6
Okonomisk Institut, KObenhavns Universitet	0.471	188	0.656	176	0.471	188	0.662	182	0.662	177	1
Okonomisk institutt, Universitetet i Oslo	0.728	68	0.872	81	0.728	68	1.000	16	0.912	79	121

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Table 6 – *cont. from previous page.*

	DEA		FDH		SDEA		order-α		order-m		RePEc
Institutions	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Rank
Paris School of Econ.	1.000	1	1.000	1	1.120	3	1.412	5	1.255	2	186
Peter G. Peterson Institute for International Econ. (IIE)	0.996	9	1.000	1	0.996	9	1.000	16	1.000	33	180
Research School of Econ., College of Business and Econ., Australian National U	0.765	52	0.863	86	0.765	52	0.863	101	0.876	91	137
Rotman School of Management, U of Toronto	0.635	136	0.701	165	0.635	136	0.701	170	0.717	165	53
SaÃ¯d Business School, Oxford U	0.843	29	1.000	1	0.843	29	1.000	16	1.000	33	160
School of Business and Econ., Maastricht U	0.659	122	0.679	174	0.659	122	0.817	126	0.753	152	67
School of Business and Econ., Universidade Nova de Lisboa	0.605	154	0.694	168	0.605	154	0.694	173	0.697	172	35
School of Business and Econ., Vrije Universiteit Amsterdam	0.743	60	0.747	148	0.743	60	0.900	92	0.817	122	129
School of Business, Management and Econ., U of Sussex	0.715	77	0.755	145	0.715	77	0.909	88	0.822	117	112
School of Econ. and Finance, Queen Mary U of London	0.622	144	0.702	164	0.622	144	0.702	169	0.719	164	45
School of Econ. and Management, Universiteit van Tilburg	0.763	53	1.000	1	0.763	53	1.322	7	1.141	6	136
School of Econ., Faculty of Arts and Social Sciences, U of Sydney	0.574	171	0.765	137	0.574	171	0.796	138	0.779	141	18
School of Econ., Finance and Management, U of Bristol	0.608	151	0.732	153	0.608	151	0.761	155	0.745	156	38
School of Econ., U College Dublin	0.752	56	0.798	124	0.752	56	0.798	136	0.799	130	133
School of Econ., U of Manchester	0.702	88	0.856	91	0.702	88	0.856	106	0.858	101	101
School of Econ., U of Nottingham	0.709	84	0.930	64	0.709	84	0.985	63	0.956	60	105
School of Econ., U of Queensland	0.802	41	0.861	87	0.802	41	1.000	16	0.930	70	148
School of Econ., U of Surrey	0.607	153	0.691	170	0.607	153	0.691	175	0.694	173	36
School of Econ., UNSW Business School, UNSW (Australia)	0.698	93	0.814	113	0.698	93	0.814	127	0.819	120	96
School of International and Public Affairs (SIPA), Columbia U	0.951	13	1.000	1	0.951	13	1.000	16	1.000	33	176
School of Management, Yale U	0.767	51	1.000	1	0.767	51	1.000	16	1.000	33	138
Sciences economiques, Sciences Po	1.000	1	1.000	1	1.092	4	1.423	3	1.118	8	185
Sloan School of Management, Massachusetts Institute of Technology (MIT)	0.701	89	1.000	1	0.701	89	1.000	16	1.004	28	100
Solvay Brussels School of Econ. and Management, Universite Libre de Bruxelles	0.705	87	0.980	53	0.705	87	1.000	16	1.020	20	102
Stern School of Business, New York U (NYU)	0.620	146	0.681	173	0.620	146	0.930	80	0.744	157	43
Tinbergen Instituut	0.840	30	1.000	1	0.840	30	1.019	14	1.011	25	159
Toulouse School of Econ. (TSE)	0.714	78	0.799	123	0.714	78	0.980	65	0.919	74	111
Universita Commerciale Luigi Bocconi	0.662	119	1.000	1	0.662	119	1.263	9	1.144	5	70
UNSW Business School, UNSW (Australia)	0.667	115	0.876	79	0.667	115	0.969	68	0.919	73	74
Vancouver School of Econ., U of British Columbia	0.873	20	1.000	1	0.873	20	1.000	16	1.011	26	169
Volkswirtschaftliche Fakultät, Ludwig-Maximilians-Universität München	0.552	176	0.734	152	0.552	176	0.763	154	0.749	153	13
W.P. Carey School of Business, Arizona State U	0.639	134	0.888	72	0.639	134	0.892	96	0.890	84	55

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Table 6 – *cont. from previous page.*

	DEA		FDH		SDEA		order-α		order-m		RePEc
Institutions	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Rank
Walter A. Haas School of Business, U of California-Berkeley	0.815	37	0.939	62	0.815	37	0.939	78	0.948	64	152
Warwick Business School, U of Warwick	0.712	82	0.775	133	0.712	82	0.775	149	0.776	142	107
Wharton School of Business, U of Pennsylvania	0.685	102	0.983	52	0.685	102	1.000	16	0.998	50	87
Wirtschaftswissenschaftliche Fakutät, Universität Zürich	0.501	185	0.852	95	0.501	185	0.955	73	0.916	75	4
Wirtschaftswissenschaftlicher Fachbereich, Rheinische Friedrich-Wilhelms-Universität Bonn	0.572	172	0.688	172	0.572	172	0.688	178	0.692	174	17
WU Wirtschaftsuniversität Wien	0.667	116	0.884	73	0.667	116	0.919	84	0.901	80	73
WU Wirtschaftsuniversität Wien	0.007	183	0.012	179	0.007	183	0.016	183	0.013	181	162

Notes: This table reports efficiency scores and corresponding ranks for each efficiency analysis. The names refer to the official listing on the RePEc website. Abbreviations are added by the authors. *RePEc* refers to the RePEc ranking explained in section 3.