Belarusian Economic Research and Outreach Center

Working Paper Series

BEROC WP No. 016

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July 2012

Working Paper Series 016

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Minsk, July 2012

Belarusian Economic Research and Outreach Center is created in Kyiv as a joint project of the Stockholm Institute of Transition Economics, the Kyiv School of Economics, the Kyiv Economics Institute and the Economics Education and Research Consortium.

It is financed jointly by the Swedish International Development Cooperation Agency (SIDA) and by the United States Agency for International Development (USAID) through the Eurasia Foundation.

Productivity analysis of Belarusian higher education system

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Abstract

In this paper we explore the issue of the measurement of productivity in the context of higher education. We suggest applying data envelopment analysis (DEA) to estimate the productivity scores for universities of Belarus. This assessment will help to find out (a) if it possible to construct alternative tier-based ratings using DEA and peeling procedure; (b) what determines the difference in productivity between public and private universities; (c) what policy should be undertaken in order to improve the performance of universities.

JEL classification: C14; D24; I21

Keywords: Universities; Ratings; Data envelopment analysis; Super-efficiency; Assuarance region; Peeling

1 Introduction

Today it is worth remembering that the development of a modern "knowledge economy" reflects a larger transition from an economy based on land, labor and capital to one in which the main components of production are information and knowledge. Some studies show that return rates on investments in education are higher than real interest rates (for details see, e.g., Schleicher (2006)). Because of that, the most effective modern economies will be those which produce the most information and knowledge — and make that information and knowledge easily accessible to the greatest number of individuals and enterprises. Thus, universities are who called upon to settle this task in the first place.

The level of competition at the market of educational services is growing both in individual countries and in the world in whole. Recognizability of the higher educational institutions, the prestigiousness of their services and the reputation at the national and international market becoming the key factors of their competitive success.

Modern university in order to be competitive and generally up-to-date has to demonstrate ability to produce moderate outputs from limited inputs, i.e. has to have acute level of productivity. The higher education sector, however, has some features which make it difficult to measure productivity: it is non-profit making; universities produce multiple outputs (e.g. education, academic research, policy recommendations, etc.) from multiple inputs (e.g. governmental and donor support, faculty and staff, facilities, etc); it is multi-purposed.

Higher education is probably the most important driving force of formation of the society able to stand the economic, political and social challenges of today. Our understanding of the relative performance of the higher education institutions (HEIs) that adopted different patterns of development would allow to come up with the recommendations to the policy makers on the optimal path of the educational reforms that leads to more competitive and productive university education. In addition, our understanding of what drives productivity of higher education will enable to provide with the policy recommendations on challenges and opportunities that exist nowadays and may impact such educational reforms.

The major approach to analyzing the performance of universities is their ranking based on weighted criteria convolution. It includes the most widely cited Academic Ranking of World Universities (ARWU)[1], QS World University Ratings[2] and other. All treatments like this has essential drawbacks, such as using mixture of inputs and outputs, unclear or arguable weighting scheme, unaccounted scale effects, absence or facilitation of classification procedure (for detailed discussion, see, e.g., Turner (2008) or Billaut et al. (2010)).

Another approach to assessments of universities' performance is productivity analysis. The theoretical basis of modern productivity analysis, based on the consideration of production as a set of processes, was laid in Koopmans (1951) and Debreu (1951). Farrell (1957) suggested the universal index, suitable for any type of organizations, for measuring the effectiveness of an arbitrary production unit (DMU — Decision Making Unit) "from the studio to the whole economy", which makes some input factors or resources (inputs) in the output factors or products (outputs).

[1] `http://www.arwu.org`

[2] `http://www.topuniversities.com/university-rankings`

Koopmans (1951) introduced the concept of input and output orientation of model. Input orientation implies that the output variables are fixed and the task is to minimize inputs, i.e. to solve the problem of search for "function of the minimum cost of production" or "minimum use of resources". Output-oriented model, by contrast, is looking for maximum production with fixed resources.

One of the most common way to estimate a deterministic production frontier and efficiency scores is data envelopment analysis (DEA), introduced in Charnes et al. (1978). Under this method we can construct a piecewise linear production frontier on experimental data with respect to which the efficiency of DMU can be measured. In an early version of the DEA, which is also called CCR — by the first letters of the names of its authors, — it was assumed constant return to scale on the final product (CRS — Constant Returns to Scale). In Banker et al. (1984) DEA model was modified to account for the variable return to scale (VRS — Variable Returns to Scale). This version is often referred to as the BCC model.

In case of input-oriented model, the efficiency score of Farrell-type takes values from 0 to 1 and indicates how unit may proportionately reduce the use of their resources for a fixed amount of production. Often in practice the metric defined by Shephard (1970) used instead, which is the reciprocal to the Farrell's metric.

Data envelopment analysis in recent years became a popular tool for evaluating the efficiency of various production units, including universities. The application of DEA to the measuring the technical efficiency of national universities can be found, e.g., in Abbott and Doucouliagos (2003) for Australia, Johnes (2006) for England. Carrico et al. (1997) demonstrated how DEA can be used to produce customized individual league tables of UK universities, Bougnol and Dulá (2006) examined DEA as a ranking tool in contrast to well-known ranking "Top American Research Universities" and found DEA suitable tool for these types of studies.

One of the main drawbacks of nonparametric deterministic methods is the difficulty in providing the statistical inference for performance evaluations, as their properties are still not fully explored. Nevertheless, Pastor et al. (2002) proposed the test to estimate the significance of variables for nested DEA-models; Simar and Wilson (2001) suggested the set of tests for detection of irrelevant inputs and outputs as far as for finding whether variables can be aggregated; using bootstrap methods adapted for the DEA-models by Simar and Wilson (2000) it is possible to construct confidence intervals for the efficiency scores.

To avoid unacceptable weighting scheme it's a good way to use multiplier restrictions. Among several ways to restrict multipliers it's widely used assurance region approach as developed by Thompson et al. (1986).

Producing tier-based ranking requires additional model. Bougnol and Dulá (2006) validated DEA as a ranking tool and found that it performs in a suitable way if compared to alternative approaches. Thus we can produce tiers of DMUs using proposed algorithm. To rank efficient units it is concept of super-efficiency, proposed by Andersen and Petersen (1993) often applied. Their model is identical to classical BCC-model, except that the unit under evaluation is not included into the reference set.

Section 2 describes the estimation framework we used, section 3 summarize data on Belarusian universities, section 4 shows major results and introduce discussion.

2 Estimation framework

We use DEA (BCC-model) as a basic tool for all estimations, so far some modifications are needed in order to receive reasonable results. The underlying estimation framework implies carrying out the following steps:

1. Restricting output multipliers and estimation of full model (i.e. we use all available inputs and outputs).
2. Reducing the dimensionality, or estimation of reduced model that can substitute the full model.
3. Peeling or tiers construction. Each tier consists of efficient units that are excluded from the data on the next step of peeling.
4. Ranking of efficient units within each tier on the basis of super-efficiency measure.

We are describing DEA methodology and related approaches below.

2.1 Data Envelopment Analysis

In terms of productivity analysis production set $\mathbf{\Psi}$ can be defined as:

$$\mathbf{\Psi} = \left\{(x,y) \in \mathbf{R}_+^{p+q} | x \text{ can produce } y\right\}, \tag{1}$$

where $x \in \mathbf{R}_+^p$ — vector of p inputs, $y \in \mathbf{R}_+^q$ — vector of q outputs.

For production set $\mathbf{\Psi}$ Farrel-type efficiency $\lambda(x,y)$ for any unit can be obtained as:

$$\lambda(x,y) = \sup\{\lambda | (x, \lambda y) \in \mathbf{\Psi}\}, \tag{2}$$

where $\lambda(x,y)=1$ indicates DMU on a production frontier, but $\lambda(x,y)>1$ indicates a possible proportional increase in production in case of elimination of inefficiency.

In practice $\mathbf{\Psi}$ and, accordingly, $\lambda(x,y)$ is unknown, so they must be estimated for some empirical data χ_n:

$$\chi_n = \left\{(x_i, y_i), i = \overline{1,n}\right\}. \tag{3}$$

where n — number of DMUs.

Estimation of feasible set $\widehat{\mathbf{\Psi}}_{DEA}(\chi_n)$ for BCC–model using DEA can be obtained solving:

$$\begin{aligned}\widehat{\mathbf{\Psi}}_{DEA}(\chi_n) = \Big\{(x,y)\in \mathbf{R}_+^{p+q} | y \le \sum_{i=1}^{n}\gamma_i y_i, x \ge \sum_{i=1}^{n}\gamma_i x_i,\\ \sum_{i=1}^{n}\gamma_i = 1, \gamma_i \ge 0, i=\overline{1,n}\Big\},\end{aligned} \tag{4}$$

where γ_i — data-driven weights for ith unit.

For any DMU (x_0, y_0) output-oriented Farrel-type scores $\widehat{\lambda}_0(x_0, y_0)$ can be obtained as:

$$\widehat{\lambda}_0(x_0,y_0) = \max_{\gamma_1,\gamma_2,\dots,\gamma_n}\left\{\lambda \ge 1 | (x_0, \lambda y_0)\in \widehat{\mathbf{\Psi}}_{DEA}(\chi_n)\right\}. \tag{5}$$

In our estimation framework we use output-oriented BCC-model as described above.

2.2 Dimensionality reduction

The widely used approach for dimensionality reduction was described in Pastor et al. (2002). As proposed, the Pastor's test applicable for radial DEA-models, thus we can test just one either input or output variable to be omitted at once.

The basic concept of the test is to compare efficiency scores of full and reduced model (where one variable is excluded). If it's no significant difference we can substitute full model with reduced.

Formally, let p_0 — is a minimal share of DMUs whose efficiency scores should be changed in, at least, $\overline{\rho}$ times. Pastor et al. (2002) recommends to use p_0=0.15 and $\overline{\rho}$=1.1. Thus, null hypothesis will be:

$$H_0 : p \leqslant p_0, \tag{6}$$

where p — is observed share of DMUs, whose scores were changed in more than $\overline{\rho}$ times.

Then, alternative hypothesis:

$$H_1 : p > p_0. \tag{7}$$

The algorithm is as following:

1. Set p_0 and $\overline{\rho}$.
2. Estimate efficiency scores for full model ϕ_j^t, $j = \overline{1, N}$, where N — number of DMUs.
3. Estimate efficiency scores for reduced model ϕ_j^r, $j = \overline{1, N}$.
4. Compute the ratio:
$$\rho_j = \frac{\phi_j^r}{\phi_j^t}, j = \overline{1, N}. \tag{8}$$
5. Check if the number of DMUs with efficiency scores higher than threshold:
$$T_j = \begin{cases} 1, \text{if } \rho_j > \overline{\rho}, \\ 0, \text{otherwise.} \end{cases} \tag{9}$$
6. Get total number of DMUs with significantly changes scores:
$$T_0 = \sum_{j=1}^{N} T_j. \tag{10}$$
7. Compute the p-value:
$$\text{p-value} = 1 - F(T_0 - 1, N - 1, p_0), \tag{11}$$
where $F(\cdot)$ — cumulative binomial function.
8. If p-value less, than comfortable 0.10 (0.05, 0.01), then reject H_0.

2.3 Assuarance region DEA (AR-DEA)

There are several approaches in literature how to restrict multipliers in order to prevent unreasonable weighting schemes.

The concepts was developed in Thompson et al. (1986) to prohibit large differences in the values of multipliers, and imposes constraints on the relative magnitudes of those multipliers. For example, one might add a constraint on the ratio of multipliers for a pair of inputs 1 and 2, in the form:
$$L_{12} \leqslant \gamma_2/\gamma_1 \leqslant U_{12} \tag{12}$$
where L_{12}, U_{12} are lower and upper bounds, respectively, on the ratio γ_2/γ_1.

The imposition of such multiplier restrictions leads to a worsening of efficiency scores, but on the other hand prevents overstating of efficiency scores for those units which have disproportional biased inputs or outputs.

2.4 Peeling procedure

Peeling procedure as proposed by Bougnol and Dulá (2006) is very intuitive process aimed at step by step excluding of efficient units from dataset. It seems as if each iteration all DMUs with efficiency score equal to 1 are "peeled" from the respective production frontier.

Figure 1 shows output space for 11 DMUs, A-K accordingly.

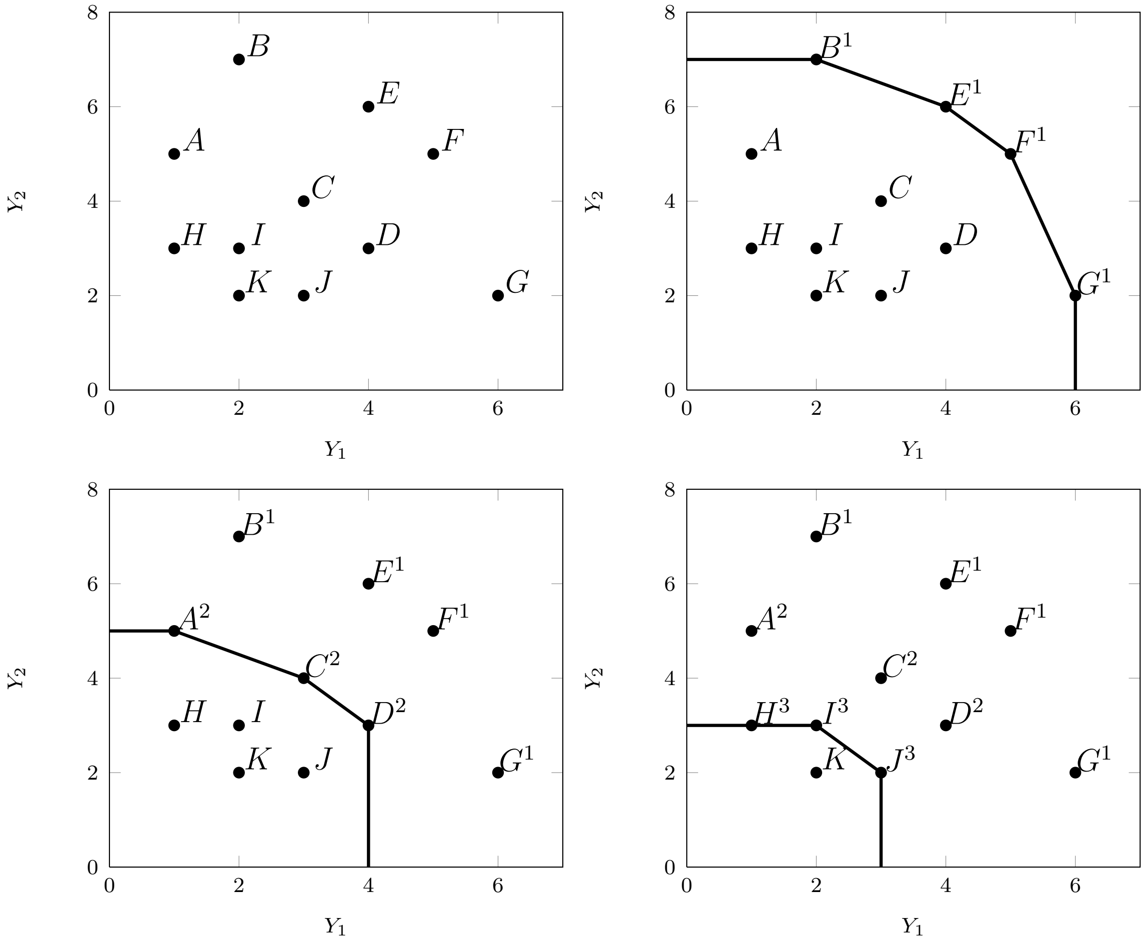

Figure 1: Three stages of peeling

At the very first step units B, E, F and G are "peeled" as far as they have efficiency score equal to unity. Before the next stage of peeling these units are excluded from the data. Second step shows A, C and D to be efficient, thus they form second tier of DMUs.

Number of stages depends on how many observations we have and dimensionality of output space, but in any case it should be clear difference between units in neighbor tiers.

2.5 Super-efficiency

An important problem in the DEA literature is that of ranking those DMUs deemed efficient by the DEA model, all of which have a score of unity. One approach to the ranking problem is that provided by the super efficiency model of Andersen and Petersen (1993).

The super-efficiency model involves executing the standard DEA models (CCR or BCC), but under the assumption that the DMU being evaluated is excluded from the reference set. In the output-oriented case, the model provides a measure of the proportional decrease in the outputs for a DMU that could take place without destroying the "efficient" status of that DMU relative to the frontier created by the remaining DMUs — sort of a measure for "margin of safety" (see Cook and Seiford (2009) for details).

3 Data

The study looks on micro-data from Belarusian universities. We have collected and studied a dataset of inputs and outputs on Belarusian economy for 2004 that came from Ministry of Education of Belarus and Special Survey of universities in 2004. We use this data as an example to outline the data specifics and methodology.

Inputs

Traditionally (Bonaccorsi et al. (2006) etc.), the analysis of resources of universities distinguishes the following micro-indices: faculty and students (Human capital), logistical and information base (Physical capital), financial resources (Financial capital).

There were considered following variables in the first micro-index: full-time equivalent of faculty (PROFESSORS), the number of administration stuff (ADMIN), adjusted number of students (STUDENTS), calculated as the total number of full-time students plus the half of the number of part-time students. When forming the second micro-index we took into account such indicators as: total area of teaching and laboratory facilities of university (SPACE), the number of units of literature in the university libraries (VOLUMES) and the total number of computers in university (COMPUTERS). To assess the financial capital of educational institutions we involved expenditures on salaries of faculty (EXP_SALARY), the cost of research work (EXP_RESEARCH) and the cost of updating the library collection and equipment (EXR_LIBRARY_EQUIP).

After preliminary analysis variables VOLUMES and COMPUTERS were excluded as its value were very improbable, possibly, due inaccurate reporting. Expenditures on salaries, library and research were combined in a single variable — EXPENDITURES, as far as original ones were strongly correlated.

Outputs

The performance of universities can be evaluated by two micro-indices: training (Teaching) and scientific activity (Research). The adjusted number of high school graduates (GRADUATES) can be one of the best indicators for assessing the productivity of training specialists. The impact of scientific activity was measured by quantity of publications by academic staff and postgraduate students. In our work we look on the number of published books (BOOKS) and publications in national journals only (ARTICLES), since publications in the Western peer-reviewed journals are rare in Post-Soviet universities.

We find the number of book to be an unfavorable measure of output because of a huge variation in the data.

Number of citations and citation indices (e.g., h-index) are widely used to compare performance of scholars or scientific units[3]. However, in case of post-Soviet countries, number of citations is not good variable as soon as there is no available data on citation of publication in national journals. On the other hand, international databases (such as *Thomson Scientific*[4] or *Scopus*[5]) contain little of records for publications of CIS's scholars, moreover their affiliations are often unclear.

Descriptive statistics for the remaining variables is shown in Table 1.

Table 1: Data description

Variable	Mean	Median	Max	Min	St.dev.
Inputs (p=4)					
PROFESSORS	420	321	1 826	56	358
STUDENTS	4 774	3 695	20 955	496	4 195
SPACE	19 051	13 258	84 347	2 075	18 008
EXPENDITURES	3 444	1 915	29 659	277	5 709
Outputs (q=2)					
GRADUATES	925	778	4 182	58	894
PUBLICATIONS	379	154	4 197	5	670

[3] To verify this one can query for "h-index" in `http://scholar.google.com`

[4] `http://science.thomsonreuters.com`

[5] `http://www.scopus.com`

4 Empirical results

All estimations in our work were made using AR-DEA output-oriented models. We allowed free weighting schemes for inputs, but restricted output space — each component could have share from 0.4 to 0.6.

We conducted Pastor test (Pastor et al. (2002)) with following parameters p_0=0.15 and $\overline{\rho}$=1.1 in order to reduce the initial dimensionality of the problem. In Table 2 presented all models with p-value of the test higher than 0.10.

Table 2: Pastor's test results

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
PROFESSORS		x	x	
STUDENTS	x	x	x	x
SPACE		x		x
EXPENDITURES	x		x	x
GRADUATES	x	x	x	x
PUBLICATIONS	x	x	x	x
P−value	0.6167	0.7636	0.9487	0.9966

Quite obviously, Model 4 was selected as far as it reproduces full model very closely. Briefly, results of Model 4 estimation presented in Table 3.

Table 3: Major results of first-stage estimation

Efficiency	Number of universities	Public	Private
0.8–1	25	19	6
0.6–0.8	13	11	2
0.4–0.6	9	9	–
$\leqslant$0.4	3	1	2

Results in Table 3 contrast to already known research outputs. For instance, Johnes (2006) found that overall mean technical efficiency of Britain universities is over 0.90; Abbott and Doucouliagos (2003) demonstrated that about 78 percent of Australian universities have efficiency over 0.90.

We ran peeling process in a manner, described in section 2. We ended up with six stages of peeling, statistics presented in Table 4. It's easy to observe, that while total number of efficient DMUs decreases during peeling process, their share strongly increases.

Table 4: Peeling process

Stage of peeling	Number of HEIs	Efficient HEIs
1	50	11
2	39	11
3	28	9
4	19	7
5	12	8
6	4	4

Alternative way of diving into peeling statistics is analysis of efficiencies' distribution. On Figure 2 you can observe evolution of efficiency scores while excluding highly productive units.

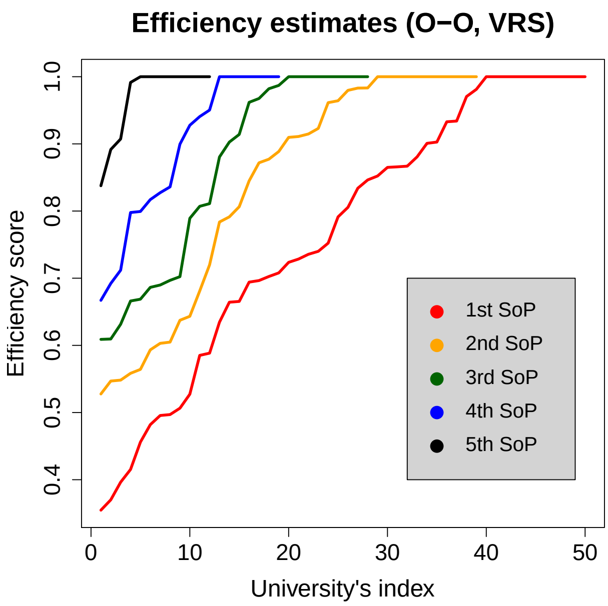

Figure 2: Peeling and efficiencies

Peeling allows to produce alternative tier-based rankings of universities. The results, driven from this approach, can strongly contradict usual ordering by BCC-score. Figure 3 clearly illustrates it, units from different stages find their places on the density curves with visible intersections of tiers.

The same logic goes for types of universities (see Figure 4). It is not significant differences between public and private HEIs in terms of mean scores (0.78 for private and 0.76 for public) as far as placements on density curves.

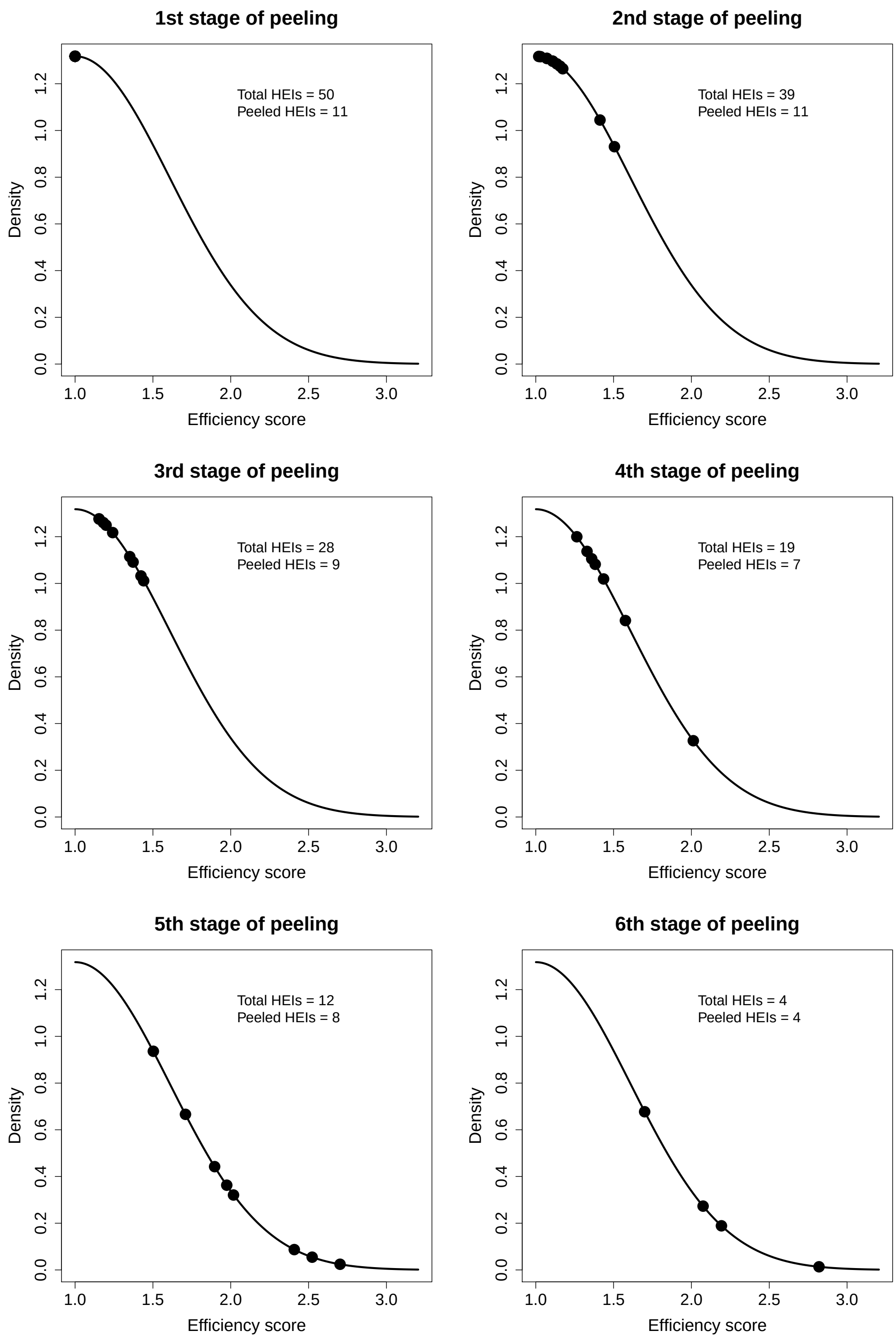

Figure 3: Kernels: Stage of peeling

Finally, all major results were combined in Table 5. Striking enough that leaders of the ranking were small and private institutions with a considerable reserve in efficiency (see column "Super-efficiency"). Minus infinity super-efficiency score for Envila is well-known situation, it means that this unit can be treated as extremely productive.

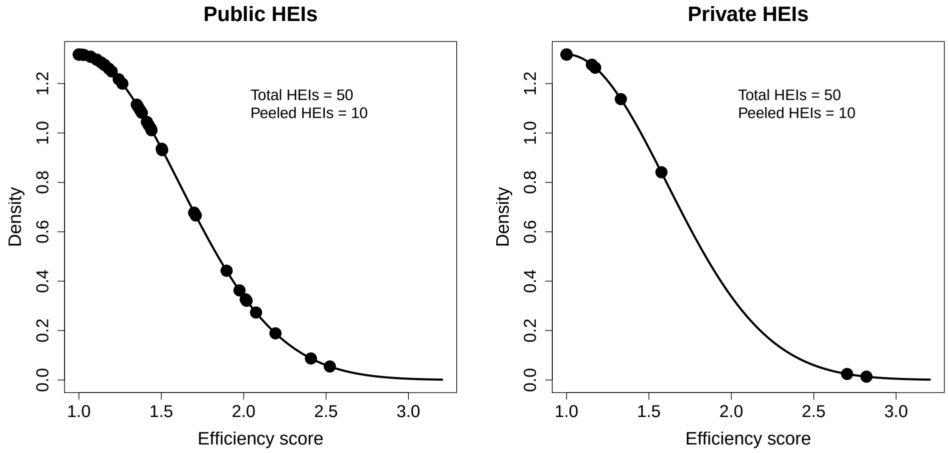

Figure 4: Kernels: Public vs private

5 Conclusion

Thus, the authors propose a method of competitiveness indices of universities construction, based on the DEA scores. Unlike methods based on weighted linear convolution, this approach allows to evaluate how effectively educational institutions use their resources to achieve the targets.

As the most important resources, disposable by universities, the authors propose to use the full-time equivalents of faculty and students, a total area of teaching and laboratory facilities and expenditures on faculty's salary, purchasing of equipment and maintenance of the library collection.

To assess the impact of HEIs' activity we use two indicators: the adjusted number of graduates and total number of published articles in refereed journals and academic published books with the stamp of the Ministry of Education.

Calculation of the experimental index of competitiveness for Belarusian universities for the academic year 2006/2007 has shown that this technique can be used to assess the effectiveness of resource usage by HEIs. In particular, the analysis has shown that difference between competitiveness of private and public schools in terms of resources utilization is merely non-existent.

Once the estimates of the common technological frontier of the higher education are obtained, it becomes possible to carry out two simple but very informative exercises. Firstly, we will test whether universities in different countries indeed share the same technological frontier, i.e. if there is a statistical difference between productivity of universities in different countries. This test will be executed using the methodology proposed by Simpson (2005). Secondly, it is possible to construct different types of relative rankings of

Table 5: General results

HEI	Place	Type	Stage of peeling					Tier	Super-efficiency
			eff.1	eff.2	eff.3	eff.4	eff.5		
Envila	1	Private	1.00					1	-Inf
MGVAK	2	Public	1.00					1	0.22
MITSO	3	Private	1.00					1	0.38
KIIMCS	4	Public	1.00					1	0.50
BGU	5	Public	1.00					1	0.63
BTEUPK	6	Private	1.00					1	0.64
MGEU	7	Public	1.00					1	0.81
BGPU	8	Public	1.00					1	0.81
BGEU	9	Public	1.00					1	0.83
BrGU	10	Public	1.00					1	0.92
ISZ	11	Private	1.00					1	0.93
BNTU	12	Public	1.11	1.00				2	0.48
BGMU	13	Public	1.03	1.00				2	0.69
AMVDRB	14	Public	1.02	1.00				2	0.76
BGUK	15	Public	1.11	1.00				2	0.87
MGEI	16	Private	1.17	1.00				2	0.87
VGU	17	Public	1.07	1.00				2	0.88
GrGU	18	Public	1.16	1.00				2	0.88
MGPU	19	Public	1.51	1.00				2	0.89
BGTU	20	Public	1.14	1.00				2	0.93
BGKS	21	Public	1.07	1.00				2	0.94
BGUIR	22	Public	1.41	1.00				2	0.96
БГАФК	23	Public	1.42	1.02	1.00			3	0.68
ПГУ	24	Public	1.18	1.02	1.00			3	0.79
ГГУ	25	Public	1.44	1.15	1.00			3	0.84
БИП	26	Private	1.15	1.04	1.00			3	0.85
ВГВАМ	27	Public	1.15	1.02	1.00			3	0.93
ГГТУ	28	Public	1.37	1.09	1.00			3	0.94
АУПРБ	29	Public	1.20	1.04	1.00			3	0.95
ВГТУ	30	Public	1.35	1.10	1.00			3	0.95
ВАРБ	31	Public	1.24	1.13	1.00			3	0.96
BrGTU	32	Public	1.44	1.28	1.11	1.00		4	0.77
BarGU	33	Public	1.26	1.08	1.02	1.00		4	0.81
CIUP	34	Private	1.58	1.18	1.04	1.00		4	0.83
VGMU	35	Public	1.36	1.10	1.03	1.00		4	0.87
BGATU	36	Public	1.38	1.24	1.09	1.00		4	0.92
IPD	37	Private	1.33	1.14	1.01	1.00		4	0.96
MGU	38	Public	2.01	1.47	1.24	1.00		4	0.99
MGUP	39	Public	1.90	1.66	1.50	1.25	1.00	5	0.74
BGVRK	40	Public	1.50	1.26	1.14	1.11	1.00	5	0.75
BRU	41	Public	1.71	1.55	1.27	1.05	1.00	5	0.76
MIU	42	Private	2.70	1.79	1.58	1.08	1.00	5	0.82
GrGAU	43	Public	2.52	1.65	1.42	1.25	1.00	5	0.85
BGUT	44	Public	1.97	1.83	1.44	1.21	1.00	5	0.89
GrGMU	45	Public	2.02	1.57	1.45	1.22	1.00	5	0.94
MGSA	46	Public	2.41	1.82	1.46	1.06	1.00	5	0.94
BGAI	47	Public	2.07	1.69	1.50	1.44	1.19	6	1.00
BGAM	48	Public	1.70	1.39	1.23	1.20	1.01	6	1.00
GGMU	49	Public	2.19	1.77	1.64	1.50	1.12	6	1.00
IPP	50	Private	2.82	1.90	1.64	1.40	1.10	6	1.00

the universities based on the multi-output model of the technological process rather than single-output models used in most of the other ranking. This will be done using so-called DEA peeling procedure as proposed by Wilson (1993) and procedure proposed by Bougnol and Dulá (2006).

At last, after estimating second-stage regression we will be able to answer if there are any measurable environmental factors that can effect productivity of universities. These results help to work out policy recommendations for governmental bodies.

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