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The global production frontier of universities

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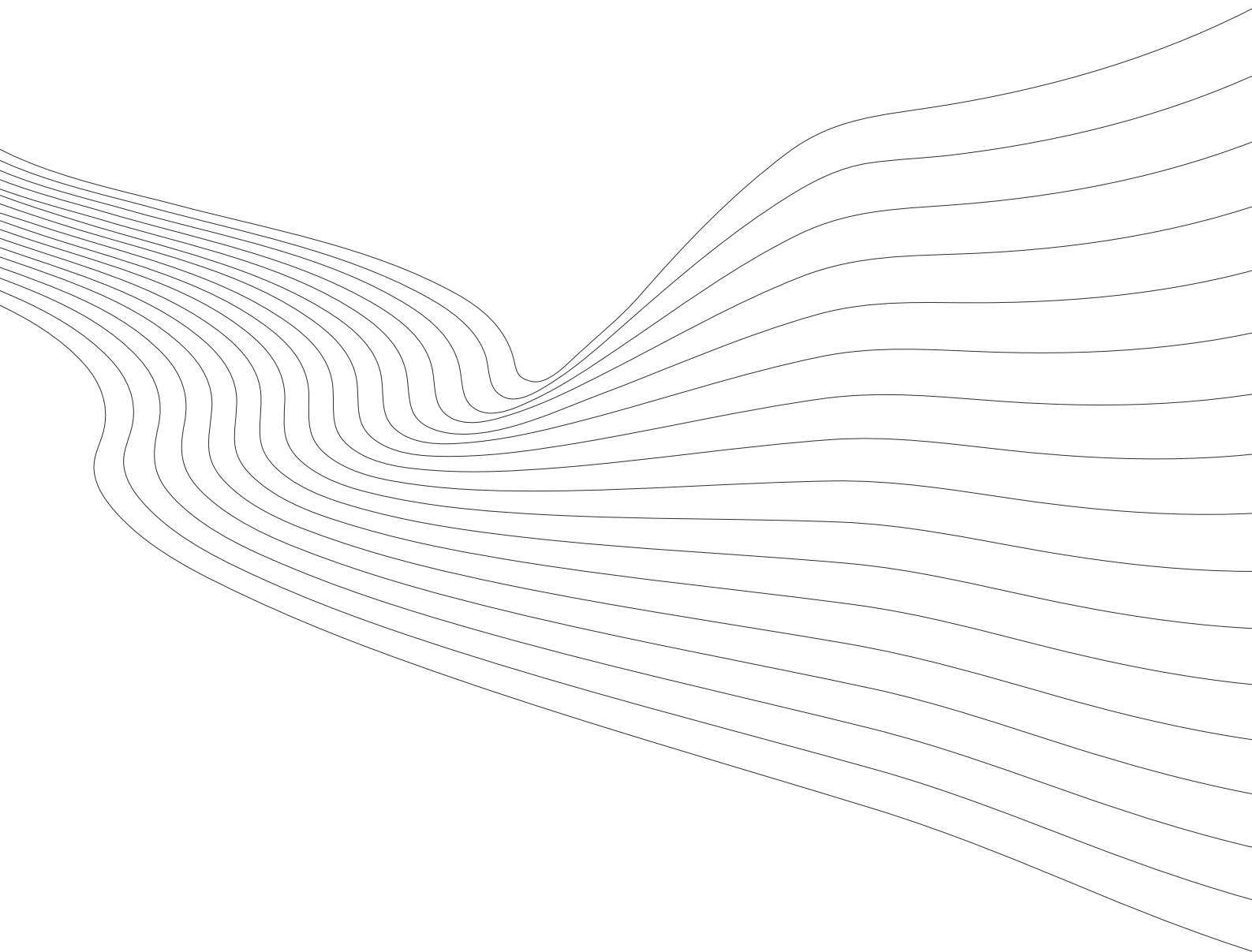
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KOF Working Papers

The Global Production Frontier of Universities

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The Global Production Frontier of Universities**

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February 2011

Abstract

This paper provides first micro-level evidence of the global university production frontier, allowing to estimate technical efficiencies of 273 top research universities across 29 countries between 2007 and 2009. Exploiting comparable international data improves the estimation of the production technology, allows to assess the distance of individual countries to the global frontier and enables comparison of university efficiencies between and across countries. The estimated input distance function uses undergraduate students, graduate students and citations to capture university outputs and staff to measure inputs. Contrasting two alternative econometric strategies to identify technical efficiency yields relatively stable results. Furthermore, the paper addresses the problem of unobserved heterogeneity by relating the obtained efficiency rankings to quality rankings and by exploiting the panel structure of the data to account for unobserved heterogeneity explicitly. The results suggest that technical efficiency rankings can be obtained in a relatively simple econometric setting.

Key words: University, Global Frontier, Efficiency, Stochastic Frontier, Unobserved Heterogeneity, True Random Effects Stochastic Frontier.

JEL Classification: D20, I20

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1 Introduction

The globalization of teaching, research and innovation activities and the corresponding internationalization of the academic world has sparked an increasing demand for comparisons of university quality across countries. The appearance of the QS World University Rankings (QS, 2010) and the Academic Ranking of World Universities (ARWU, 2010) represent the most famous responses to these developments. These two rankings have received substantial interest of the public. They also created a new literature strand that criticizes the employed methodology (see, e.g., Dill and Soo, 2005; Marginson and van der Wende, 2007; Stolz et al., 2010). Furthermore, the rankings evoked a discussion concerning the incentives they create (see, e.g., Hazelkorn, 2007; Clarke, 2007).

However, quality of universities measured by these rankings reflects only one dimension relevant to politicians. The other side of the coin shows the productivity and efficiency in the production process of universities. Hence, complementing these rankings, the literature on university efficiency has grown rapidly as Agasisti and Johnes (2010) and Johnes and Johnes (2009) demonstrate. Worthington (2001) and Johnes (2004) provide literature reviews. However, only few studies provide cross-country evidence and no global production frontier has been established yet (Agasisti and Johnes, 2009).

This paper applies the production function framework to an international data set provided by the QS World University Rankings (QS, 2010) to estimate a multi-output input distance function for 273 top research universities in 29 countries between 2007 and 2009. Thereby the paper extends the existing literature by providing first micro-level evidence of the global university production frontier.

Estimating a global frontier as opposed to individual national production frontiers allows to estimate a more general production technology and to assess the distance of country frontiers to the global frontier. Finally, it allows to compare technical efficiencies between and across countries. However, international comparisons faces problems of data consistency and sample homogeneity (Salerno, 2003). The employed data set circumvents these pitfalls due to the centralization of the data collection process and the uniformity of sample selection.

Furthermore, the paper uses two approaches to address the problems of quality and unobserved heterogeneity, which plague the literature on university efficiency. First, it exploits the availability of quality rankings to calculate Spearman correlations between predicted efficiency scores and quality measures based on rankings of the QS (2010). Secondly, the paper uses the true random effects stochastic frontier approach proposed by Greene (2005a,b), which exploits the panel data structure to

disentangle unobserved heterogeneity and efficiency.

The paper is structured as follows: Section 2 summarizes the existing literature. Sections 3 and 4 describe the data and the applied methodology. Section 5 discusses the estimation results. Section 6 summarizes the paper.

2 Literature

The literature on university efficiency grows rapidly. Worthington (2001) and Johnes (2004) provide literature reviews. However, little evidence in respect to cross-country comparisons exists (Agasisti and Johnes, 2009). Salerno (2003) explains that cross-country comparisons face the difficulties to obtain comparable data and to ensure institutional comparability and sample homogeneity. Hence, only few studies spanning multiple countries exist.

Joumady and Ris (2005) conducted 209 interviews of graduate students across eight European countries and use the resulting information to estimate teaching efficiency of universities using Data Envelopment Analysis (DEA). Aghion et al. (2010) do not estimate a production frontier, but compare the research productivity in US and European universities, showing that the latter lag behind according to a number of indicators. Furthermore, they find that autonomy and accountability boost productivity. Bonaccorsi and Daraio (2007) provide an in-depth analysis of university specialization and performance by exploiting the Aquameth database which contains micro-level information about universities across Europe.

In addition, the existing literature contains a small number of papers providing pairwise country comparisons. Namely, Agasisti and Johnes (2009) employ the DEA methodology to UK and Italian administrative data and demonstrate that technical efficiency of UK universities is higher. Similarly, Agasisti and Pérez-Esparrells (2009) compare the efficiency of Spanish and Italian universities and find higher efficiencies for Italian universities.

3 Data

Based on data from the QS World University Rankings (QS, 2010), this paper estimates an input distance function. Inputs enter as the number of full-time equivalent (FTE) staff.¹ The assumed production technology considers three outputs, namely

¹For observations that only entail information about headcount, the measures for FTE staff and students refer to headcount multiplied by the average ratio between headcount and FTE staff/students.

FTE undergraduate students, FTE graduate students and citations. Citations refer to the score of the ranking item "citations per employee" multiplied by the number of FTE employees.² The employed variables are normalized by the sample median. Table 1 provides summary statistics of the variables.

Table 1: *Summary statistics*

Variable	Description	Mean	Std. Dev.	Min	Max
Staff	Employees (FTE)	1810.567	1077.974	88	6637
Ugrad	Undergraduate Students (FTE)	16022.98	12367.46	173	130227
Grad	Graduate Students (FTE)	5702.221	3860.372	372.3154	32283
Cit	Index of citations within 5 years	128953.9	83184.15	4576	458874

The sample consists of universities for which an individual score for the item "citations per FTE employee" exists, i.e. the top 300 research universities. Restraining the sample to universities observed in multiple time periods and dropping observations with missing values yields a sample of 273 universities over time, resulting in 720 observations.

4 Methodology

This paper employs two alternative methodologies to identify university efficiencies. The first methodology consists of estimating a fixed effect estimator (*FE*). Schmidt and Sickles (1984) suggest to transform the predicted individual intercepts ($\hat{\alpha}_i$) by subtracting them from the maximum intercept ($\max(\hat{\alpha}_i)$) and to interpret the resulting deviations as inefficiency. This approach has the advantage that it is distribution free except for the normally distributed error term. However, it might suffer from the incidental parameter problem (Lancaster, 2000) and assumes that unobserved heterogeneity comprises only efficiency. A translog specification of the input distance function approximates production technology as specified in formula 1:

$$-\ln x_{it} = \sum_{m=1}^3 \gamma_m \ln y_{mit} + \frac{1}{2} \sum_{m=1}^3 \sum_{n=1}^3 \gamma_{mn} \ln y_{mit} \ln y_{nit} + \delta_t + \alpha_i + \nu_{it}, \quad (1)$$

The dependent variable (x_{it}) captures the number of FTE employees of university i , at time t . In line with the literature on input distance functions, x_{it} enters with a negative sign. The vector of explanatory variables entails three outputs (y_{mit}),

²Hence, this measure assumes that the citations per employee of the best university remains constant over time.

namely FTE undergraduate students, FTE graduate students and citations. Year dummies (δ_t) account for differences across time. ν_{it} refers to the traditional error term, i.e. follows a normal distribution with mean zero and variance σ_ν^2 . α_i denotes individual intercepts, i.e. university-specific dummy variables. Calculation of predicted technical efficiencies (\widehat{TE}_i) follows

$$\widehat{TE}_i = \exp(-\widehat{v}_i) = \exp(-(\max(\widehat{\alpha}_i) - \widehat{\alpha}_i)) \quad (2)$$

The second methodology to identify efficiency builds on the idea of Aigner et al. (1977) and Meeusen and van den Broeck (1977). The stochastic frontier analysis (*SFA*) identifies inefficiency by assuming that it follows a half-normal distribution. Using the same production technology as above yields the following econometric specification:

$$-\ln x_{it} = \sum_{m=1}^3 \gamma_m \ln y_{mit} + \frac{1}{2} \sum_{m=1}^3 \sum_{n=1}^3 \gamma_{mn} \ln y_{mit} \ln y_{nit} + \delta_t + \varepsilon_{it} \quad (3)$$

The error term consists of two parts, i.e. $\varepsilon_{it} = \nu_{it} + v_i$. As before, ν_{it} refers to a normally distributed error term with mean zero and variance σ_ν^2 . v_i denotes the time-invariant, half-normally distributed inefficiency term, i.e. $v_i = |U_i|$, with $U_i \sim N(0, \sigma_v)$. The methodology developed by Jondrow et al. (1982) backs out inefficiency scores according to

$$E[v|\varepsilon] = \frac{\sigma\lambda}{1+\lambda^2} \left[\frac{\phi(z)}{1-\Phi(z)} - z \right], z = \frac{\varepsilon\lambda}{\sigma} \quad (4)$$

where $\lambda = \frac{\sigma_v}{\sigma_\nu}$ and $\sigma = \sqrt{\sigma_v^2 + \sigma_\nu^2}$. As above, the exponential of negative inefficiencies yields technical efficiency scores, i.e. $\widehat{TE}_i = \exp(-\widehat{v}_i)$

While the data accounts for the quality of research using citations, a number of potential reasons for unobserved heterogeneity exists, e.g. the quality of students, education and staff. The inability of the data to identify the relative relevance of scientific fields poses an additional problem, since both the adequacy of citations to measure research output as well as the average costs of education differ across fields. Finally, various cross-country differences might influence the estimates.

In order to analyze the relevance of unobserved heterogeneity for the identification of university efficiency rankings, this paper further presents a true random effects stochastic frontier approach (*True RE SFA*), which tackles the problem of unobserved heterogeneity by adding a set of time-invariant, university-specific intercepts, α_i , to formula 3 (Greene, 2005a,b). As the estimators' name suggests, the

university-specific intercepts presumably follow a normal distribution with mean μ_α and variance σ_α^2 . Hence, the estimation can be written as:

$$- \ln x_{it} = \sum_{m=1}^3 \gamma_m \ln y_{mit} + \frac{1}{2} \sum_{m=1}^3 \sum_{n=1}^3 \gamma_{mn} \ln y_{mit} \ln y_{nit} + \delta_t + \alpha_i + \varepsilon_{it} \quad (5)$$

As before, the error term ε_{it} consists of two parts. ν_{it} refers to a normally distributed error term with mean zero and variance σ_ν^2 . Furthermore, the *True RE SFA* assumes that the second component, inefficiency, v_{it} , varies over time. Hence, the identifying distributional assumption concerning the inefficiency term becomes $v_{it} = |U_{it}|$, with $U_{it} \sim N(0, \sigma_v)$. Limdep estimates the *True RE SFA* using a simulated maximum likelihood estimator with 100 draws using Halton sequences. In order to facilitate the comparison across models, the discussion centers around time-invariant efficiency estimates calculated as the average of yearly efficiency scores.

Table 2 summarizes the assumptions underlying the three estimators employed in this paper:

Table 2: *Econometric and distributional assumptions of FE, SFA and True RE SFA*

	<i>FE</i>	<i>SFA</i>	<i>True RE SFA</i>
Heterogeneity	0	0	$\alpha_i \sim N$
Inefficiency	$\max(\alpha_i) - \alpha_i$	$v_i = U_i , U_i \sim N$	$v_{it} = U_{it} , U_{it} \sim N$

5 Results

The coefficient estimates of the econometric estimations appear in the top panel of table 4. The estimates behave well in the sense that the first-order coefficients of outputs have the expected negative sign. Furthermore, the coefficient estimates remain stable across methodologies. The bottom panel of table 4 displays the Spearman correlations between the predicted efficiency scores of alternative estimation techniques. Table 5 in section 7 displays individual university rankings of predicted efficiency scores for each methodology.

Figure 1 plots the predicted efficiencies of the fixed effects (*FE*) and stochastic frontier (*SFA*) approaches sorted by the ranking indicated by the *FE* model for each country. It reveals that the estimated levels of efficiency in the stochastic frontier framework dominate those predicted by the fixed effects model. However, comparing the ordering of the two estimators indicates a high correlation of rankings. The



Figure 1: *Distribution of efficiency scores across countries comparing FE and SFA*

lower panel of table 4 confirms this visual impression by showing a Spearman rank correlation of nearly 0.9 between the *FE* and *SFA* model. The high correlation of these two approaches to identify efficiency supports the distributional assumption of the *SFA*.

In order to facilitate the comparison of predicted efficiencies across countries, table 3 displays the mean and maximum of predicted efficiency scores in each country. However, the interpretation of these indicators requires cautiousness since our sample reflects a particular selection of universities and not the population or a representative drawing thereof.

Both the *FE* and the *SFA* estimator suggest that Israel and Switzerland have the highest mean of university efficiency. Furthermore, table 3 displays relatively stable rankings of the ten countries with the highest mean efficiency across methodologies. Calculating the average rank across the two methodologies suggests that Austria ranks third, followed by the USA, South Korea, Finland Canada, South Africa and Belgium. In addition, France and Spain appear within the top ten, but only accord-

Table 3: *Distribution of efficiency estimates across countries*

Country	N	FE		SFA	
		Mean	Max	Mean	Max
Australia	7	0.47	0.51	0.75	0.80
Austria	3	0.59	0.66	0.90	0.94
Belgium	5	0.55	0.69	0.81	0.95
Brazil	1	0.47	0.47	0.72	0.72
Canada	16	0.54	0.70	0.84	0.97
China	3	0.48	0.54	0.75	0.86
Denmark	4	0.45	0.54	0.68	0.78
Finland	3	0.57	0.64	0.82	0.86
France	9	0.59	1.00	0.73	0.90
Germany	21	0.51	0.93	0.76	0.98
Greece	2	0.51	0.59	0.75	0.85
Hong Kong	5	0.49	0.56	0.74	0.80
India	3	0.51	0.59	0.63	0.74
Ireland	1	0.37	0.37	0.58	0.58
Israel	4	0.65	0.72	0.93	0.97
Italy	9	0.49	0.58	0.78	0.92
Japan	18	0.51	0.68	0.77	0.95
Korea, South	3	0.64	0.90	0.81	0.96
Netherlands	9	0.53	0.69	0.79	0.96
New Zealand	2	0.41	0.44	0.66	0.69
Norway	3	0.44	0.52	0.67	0.77
Singapore	2	0.48	0.55	0.78	0.89
South Africa	1	0.55	0.55	0.84	0.84
Spain	5	0.50	0.60	0.81	0.93
Sweden	8	0.52	0.67	0.74	0.85
Switzerland	6	0.66	0.78	0.91	0.97
Taiwan	5	0.50	0.58	0.69	0.80
United Kingdom	28	0.45	0.53	0.72	0.81
USA	87	0.56	0.93	0.85	0.97
Total	273	0.53	1.00	0.79	0.98

The table shows the number of observations in each country as well as the mean and maximum of predicted efficiencies according to the fixed effects (FE) and stochastic frontier (SFA) methodologies.

ing to one of the two estimators. Comparing the results of medium ranked countries across the two methodologies reveals a relatively volatile order. However, the ranking turns more stable for the bottom third again, where Brazil ranks before the UK, Denmark, Norway, New Zealand and Ireland. The appearance of China, France, Singapore and Taiwan in the bottom third of the distribution depends on the employed methodology.

Comparing these results to those obtained by Joumady and Ris (2005) suggests relatively consistent efficiency estimates despite the fact that Joumady and Ris (2005) estimate teaching efficiency using the non-parametric data envelopment approach, while this paper employs a parametric framework accounting for both teaching and research. Among the overlapping countries, only two display differences between these two papers. Namely, Finland ranks low in Joumady and Ris (2005) but high according to the above results. Conversely, the UK performs well in Joumady and Ris (2005) but not in this paper.

The second measure, the maximum efficiency of a university within a country, reflects the minimum distance to the frontier and hence allows to identify the countries which form the production frontier. Similar to the comparison of mean efficiencies

across methodologies, the minimum distance to the frontier appears relatively stable among the top ten countries. However, figure 1 reveals that the distribution of efficiencies within a country differs between the two methodologies. Concretely, the maximum efficiency within a country drops relatively quickly for the *FE* methodology but remains high throughout the top universities according to the *SFA* estimator. Both estimators locate Germany and USA at the frontier. The average of ranks across methodologies places Switzerland next, followed by Israel, South Korea, Canada, the Netherlands, Belgium and Japan. France displays a high volatility as it achieves the highest value using the *FE* estimator but merely reaches the 13th rank based on the *SFA* methodology. The volatility of estimates across methodologies remains high for both the middle and the bottom third of countries.

However, the *FE* and *SFA* methodologies do not account for quality and unobserved heterogeneity. Hence, the lower panel of table 4 provides first indication whether unobserved heterogeneity biases the estimation results. It shows information about the Spearman correlations of estimated efficiency scores and measures of quality based on the QS (2010). Concretely, the displayed quality measures refer to the inverse of rankings in terms of peer and employer surveys as well as the inverse of the overall QS quality ranking. As table 4 shows, the correlations are low and even mostly positive, despite the fact that failing to account for quality adequately suggests a negative correlation between efficiency and quality. Hence, these correlations provide indicative evidence that the employed econometric methodologies account for quality in a sufficient manner.³

In order to provide a more thorough analysis of unobserved heterogeneity, table 4 further portrays the coefficient estimates of the *True RE SFA* in column 3. The estimates behave well in the sense that the first-order coefficients of outputs have the expected negative sign and resemble closely those of the *FE* and *SFA* methodologies. However, the estimated standard deviation of efficiency, σ_v , drops to merely 0.00001. Hence, the predicted efficiency scores barely vary, implying a negligible identification power of this estimator. The *True RE SFA* methodology essentially divides universities into four categories. The "University of Mannheim" obtains the highest efficiency score, followed by a group of 31 universities. Then, the estimator creates a bulk of universities that cannot be distinguished. Finally, eleven universities constitute the rear.

However, table 4 further reveals that the *True RE SFA* yields efficiency esti-

³Similarly, including quality measures in the estimation directly supports this interpretation as well. Concretely, the coefficients of quality measures turn out insignificant or even positive. Furthermore, the Spearman correlation of the resulting efficiency estimates with the unadjusted *FE* and *SFA* scores remains above 0.95.

mates with a Spearman correlation of more than 0.85 compared to the *FE* and *SFA* methodologies. The high Spearman correlation suggests that accounting for unobserved heterogeneity might not be as relevant to obtain credible efficiency ranking estimates. Hence, the robustness check of estimating a *True RE SFA* suggests that interpreting the predictions of the simpler methodologies *FE* and *SFA* appears adequate.

An interesting interpretation of the applied estimation methodologies follows Greene (2004), according to which the *FE* estimator underestimates efficiency since it labels all unobserved heterogeneity as inefficiency. The *True RE SFA* estimator on the other hand tends to capture too much of between variation in unobserved heterogeneity and hence overestimates efficiency. This interpretation suggests that the *FE* and *True RE SFA* estimators form the lower and upper boundaries for the true efficiency scores, respectively. Figure 2 displays the predicted efficiency scores for each of the three estimation techniques sorted by the *FE* efficiency scores. The predictions of the *SFA* lie within the predictions of the *FE* and the *True RE SFA* estimator. Hence, these results support the above interpretation as efficiency boundaries. Thereby, figure 2 provides further indicative evidence for the hypothesis that the *SFA* methodology yields reasonable efficiency predictions.

6 Summary

This paper applies the production function framework to an international perspective of universities by exploiting data provided by the QS World University Rankings (QS, 2010) to estimate a multi-output input distance function for 273 universities in 29 countries between 2007 and 2009. Thereby the paper extends the existing literature by providing first micro-level evidence of the global university production frontier.

The estimated input distance function uses staff to measure inputs. Outputs refer to undergraduate students, graduate students and citations. A translog specification approximates the production technology. The paper contrasts two strategies to identify technical efficiency. First, the deterministic frontier approach proposed by Schmidt and Sickles (1984) estimates a fixed effect estimator. Assuming that the highest predicted individual intercept reflects the most efficient university allows to interpret transformed intercepts as inefficiency. Secondly, the stochastic frontier approach identifies technical efficiency by assuming that it follows a half-normal distribution (Aigner et al., 1977; Meeusen and van den Broeck, 1977). The two methodologies yield relatively similar efficiency rankings estimates.

The predicted efficiency scores reveal that Israel and Switzerland display the highest average efficiency, followed by Austria, the USA, South Korea and Finland.

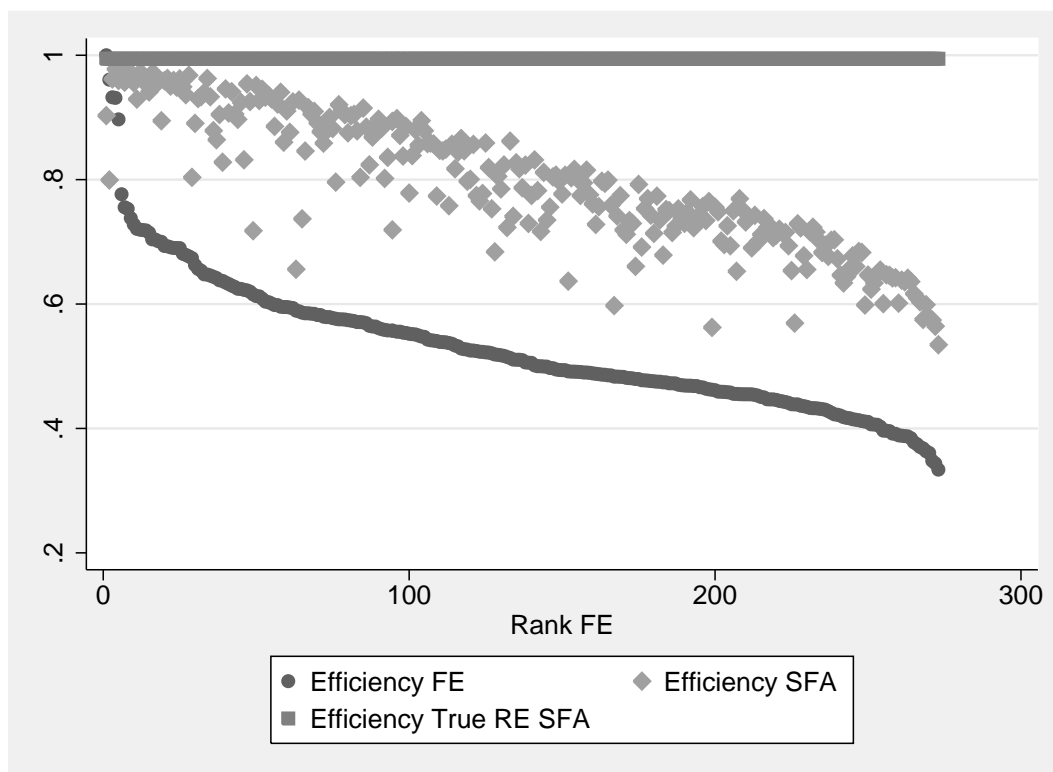


Figure 2: *Estimation boundaries of efficiency scores*

Germany and the USA, pursued by Switzerland, Israel and South Korea, form the production frontier.

Furthermore, the paper uses two approaches to address the problems of quality and unobserved heterogeneity which plague the literature on university efficiency. First, the finding that the Spearman correlation between technical efficiency scores and quality measures based on rankings of the QS (2010) is low or even positive suggests that the fixed effects and stochastic frontier approach account for quality in a sufficient manner. Secondly, the paper uses the true random effects stochastic frontier approach proposed by Greene (2005a,b), thereby exploits the panel data structure to disentangle unobserved heterogeneity and efficiency. The Spearman correlations between the three employed estimators remain high after accounting for unobserved heterogeneity, suggesting that simple estimation techniques suffice to obtain credible efficiency ranking estimates. However, by revealing that the true random effects stochastic frontier yields statistically uninformative efficiency estimates, this econometric exercise also illustrates the challenges in providing adequate information to

university managers to asses universities.

7 Tables

Table 5: Ranks of predicted university efficiencies according to FE, SFA and True RE SFA

University	j	FE	SFA	TRE	University	j	FE	SFA	TRE
AUSTRALIAN National Uni	AU	146	162	147	CHALMERS University of Tech	SE	29	123	147
University of ADELAIDE, The	AU	182	182	147	Kth. ROYAL INSTITUTE of Tech	SE	152	253	147
University of MELBOURNE	AU	232	195	147	LUND University	SE	118	99	147
University of NEW SOUTH WALES	AU	147	122	147	STOCKHOLM School of Economics	SE	63	238	147
University of QUEENSLAND,	AU	201	170	147	STOCKHOLM University	SE	195	179	147
University of SYDNEY	AU	248	228	147	UPPSALA University	SE	112	97	147
Uni of WESTERN AUSTRALIA	AU	137	138	147	Umeå University	SE	168	174	147
MCI Management Center INNSBRUCK	AT	31	37	17	Uni of GOTHENBURG	SE	250	245	147
University of GRAZ	AT	131	111	147	ETH Zurich	CH	35	35	147
University of VIENNA	AT	58	30	147	ETH LAUSANNE	CH	36	76	147
Catholic University of LEUVEN	BE	70	67	147	University of BERN	CH	61	81	147
Free University of Brussels(VUB)	BE	134	175	147	University of GENEVA	CH	18	18	17
University of GHENT	BE	272	271	267	University of LAUSANNE	CH	59	88	147
University of LIEGE	BE	24	25	17	University of ZURICH	CH	6	5	17
Universite Catholique de LOUVAIN	BE	41	52	147	NATIONAL TAIWAN Uni	TW	185	168	147
State University of CAMPINAS	BR	187	194	147	National CHIAO TUNG Uni	TW	174	235	147
DALHOUSIE University	CA	71	80	147	National SUN YAT-SEN Uni	TW	128	227	147
LAVAL University	CA	89	69	147	National TSING HUA Uni	TW	76	134	147
Mcgill University	CA	262	255	147	National YANG MING Uni	TW	226	270	267
Mcmaster University	CA	17	8	17	CARDIFF University	UK	259	249	147
QUEEN'S University	CA	160	156	147	DURHAM University	UK	162	160	147
SIMON FRASER University	CA	189	177	147	IMPERIAL College London	UK	159	144	147
The University of WESTERN ONTARIO	CA	40	26	17	KING'S College London	UK	222	209	147
University of ALBERTA	CA	216	180	147	NEWCASTLE University	UK	237	233	147
University of BRITISH COLUMBIA	CA	175	137	147	Queen's Uni of BELFAST	UK	270	267	267
University of CALGARY	CA	42	28	147	UCL	UK	153	125	147
University of MANITOBA	CA	223	208	147	University of ABERDEEN	UK	202	218	147
University of OTTAWA	CA	114	94	147	University of BATH	UK	203	220	147
University of TORONTO	CA	50	22	147	University of BIRMINGHAM	UK	196	159	147
University of VICTORIA	CA	73	79	147	University of BRISTOL	UK	156	146	147
University of WATERLOO	CA	69	51	147	University of CAMBRIDGE	UK	151	120	147
Université De Montréal	CA	106	92	147	University of DUNDEE	UK	193	197	147
FUDAN University	CN	253	243	147	University of EAST ANGLIA	UK	255	263	267
SHANDONG University	CN	108	93	147	University of EDINBURGH	UK	211	176	147
University of S&T of China	CN	145	183	147	University of GLASGOW	UK	188	165	147
AARHUS University	DK	142	140	147	University of LEEDS	UK	257	247	147
Technical Uni of DENMARK	DK	113	158	147	University of LEICESTER	UK	119	131	147
Uni of COPENHAGEN	DK	271	269	147	University of LIVERPOOL	UK	215	212	147
Uni of SOUTHERN DENMARK	DK	249	265	147	University of MANCHESTER	UK	228	199	147
KUOPIO University	FI	37	86	147	University of NOTTINGHAM	UK	263	251	267
University of HELSINKI	FI	107	90	147	University of OXFORD	UK	198	155	147
University of TURKU	FI	132	196	147	University of READING	UK	230	239	147
Claude Bernard University Lyon 1	FR	190	187	147	University of SHEFFIELD	UK	234	217	147
Ecole Normale Superieure de LYON	FR	2	129	147	University of SOUTHAMPTON	UK	210	186	147
Ecole Normale Superieure, Paris	FR	1	59	147	University of ST ANDREWS	UK	139	189	147
Joseph Fourier Uni - GRENOBLE I	FR	251	258	267	University of SUSSEX	UK	124	142	147
Paris-Sud XI University	FR	246	236	147	University of YORK	UK	186	207	147
Polytechnic School (France)	FR	49	203	147	ARIZONA STATE University	USA	206	169	147
University MONTPELLIER II	FR	207	242	147	BOSTON University	USA	135	109	147
Uni Pierre and Marie Curie	FR	267	261	267	BRANDEIS University	USA	19	65	17
University of Strasbourg	FR	72	91	147	BROWN University	USA	14	21	17
BIELEFELD University	DE	140	145	147	CARNEGIE MELLON Uni	USA	44	63	147
Free University of BERLIN	DE	82	55	147	CASE WESTERN RESERVE Uni	USA	109	149	147
University of Erlangen-Nuernberg	DE	150	143	147	COLORADO STATE University	USA	57	45	147
University of JENA	DE	243	248	147	COLUMBIA University	USA	90	62	147
Goethe Uni FRANKFURT	DE	197	184	147	CORNELL University	USA	62	43	147
HEIDELBERG University	DE	220	213	147	Caltech	USA	3	13	17
Heinrich Heine Uni of Dusseldorf	DE	98	104	147	DARTMOUTH College	USA	15	29	17
Johannes Gutenberg Uni of MAINZ	DE	20	16	17	DREXEL University	USA	260	262	147
Ludwig Maximilian - Uni of MUNICH	DE	155	127	147	DUKE University	USA	86	72	147
Ruhr University BOCHUM	DE	256	244	147	EMORY University	USA	75	74	147
Saarland University	DE	93	105	147	FLORIDA STATE University	USA	213	173	147

Technical Uni of MUNICH	DE	235	229	147	GEORGE WASHINGTON University	USA	205	223	147
University of Cologne	DE	233	206	147	GEORGETOWN University	USA	171	211	147
University of Fribourg	DE	273	273	267	GEORGIA Institute of Technology	USA	9	4	17
University of Göttingen	DE	269	264	267	HARVARD University	USA	68	53	147
University of KONSTANZ	DE	122	147	147	INDIANA University Bloomington	USA	148	119	147
University of LEIPZIG	DE	105	77	147	IOWA STATE University	USA	116	102	147
University of MANNHEIM	DE	4	1	1	JOHNS HOPKINS University	USA	67	47	147
University of Tübingen	DE	204	192	147	LOUISIANA STATE University	USA	239	215	147
University of ULM	DE	95	201	147	MICHIGAN STATE University	USA	209	167	147
University of Würzburg	DE	87	110	147	MIT	USA	22	23	17
National Technical Uni of ATHENS	GR	225	241	147	NEW YORK University (nyu)	USA	247	226	147
University of ATHENS	GR	66	101	147	NORTH CAROLINA STATE Uni	USA	53	36	147
City University of HONG KONG	HK	212	225	147	NORTHWESTERN University	USA	83	78	147
HONG KONG University of S&T	HK	92	126	147	OHIO STATE University	USA	154	116	147
The Chinese Uni of Hong Kong	HK	214	219	147	PENNSYLVANIA STATE University	USA	117	85	147
The HONG KONG Polytechnic Uni	HK	130	139	147	PRINCETON University	USA	10	19	17
University of HONG KONG	HK	219	214	147	PURDUE University	USA	163	132	147
Indian Institute of Tech Bombay	IN	199	272	267	RENSSELAER Polytechnic Institute	USA	7	17	17
Indian Institute of Tech Delhi	IN	167	266	267	RICE University	USA	11	39	147
Indian Institute of Tech KANPUR	IN	65	181	147	RUTGERS	USA	231	205	147
DUBLIN TRINITY COLLEGE	IE	268	268	267	STONY BROOK University	USA	110	98	147
BEN GURION Uni of The Negev	IL	56	70	147	Stanford	USA	23	15	17
Hebrew Uni of JERUSALEM	IL	33	31	147	TEXAS A&M Uni	USA	96	61	147
TECHNION-Israel Institute of Tech	IL	43	54	17	TUFTS University	USA	27	32	147
TEL AVIV University	IL	13	7	17	TULANE University	USA	170	202	147
Sapienza University of Rome	IT	192	153	147	University of ALABAMA	USA	48	42	17
University of FLORENCE	IT	227	190	147	University of ARIZONA	USA	79	57	147
University of PADUA	IT	77	46	147	Uni of CALIFORNIA, Davis	USA	54	33	147
University of PAVIA	IT	169	148	147	Uni of CALIFORNIA, Irvine	USA	51	41	17
University of PISA	IT	138	112	147	Uni of CALIFORNIA, Riverside	USA	25	12	17
Uni of Rome TOR VERGATA	IT	200	161	147	Uni of CALIFORNIA, San Diego	USA	16	6	17
University of SIENA	IT	111	100	147	Uni of CALIFORNIA, Santa Barbara	USA	12	3	17
University of TRENTO	IT	176	224	147	Uni of CALIFORNIA, Santa Cruz	USA	8	2	17
University of TRIESTE	IT	179	172	147	University of CHICAGO	USA	80	82	147
CHIBA University	JP	172	185	147	University of CINCINNATI	USA	136	114	147
HIROSHIMA University	JP	244	237	147	University of CONNECTICUT	USA	60	50	147
HOKKAIDO University	JP	177	163	147	BERKELEY	USA	28	9	17
KANAZAWA University	JP	161	191	147	UCLA	USA	47	20	147
KYOTO University	JP	95	66	147	Uni of Colorado at BOULDER	USA	74	60	147
KYUSHU University	JP	184	166	147	University of DELAWARE	USA	103	96	147
MIE University	JP	183	230	147	University of FLORIDA	USA	158	117	147
NAGOYA University	JP	166	157	147	University of GEORGIA	USA	218	193	147
NIIGATA University	JP	173	188	147	University of HAWAII	USA	129	121	147
OSAKA CITY University	JP	127	164	147	University of HOUSTON	USA	149	133	147
OSAKA University	JP	181	150	147	Uni of ILLINOIS at Urbana-Champaign	USA	104	64	147
TOHOKU University	JP	236	221	147	University of IOWA	USA	81	58	147
TOKYO Institute of Tech	JP	38	56	147	University of KANSAS	USA	258	250	147
TOKYO METROPOLITAN Uni	JP	84	124	147	University of KENTUCKY	USA	97	83	147
TOKYO Uni of Science (TUS)	JP	26	24	17	University of MARYLAND	USA	125	89	147
University of TOKYO	JP	208	152	147	University of MIAMI	USA	194	178	147
University of TSUKUBA	JP	252	257	147	University of MICHIGAN	USA	133	87	147
YOKOHAMA CITY University	JP	39	108	147	University of MINNESOTA	USA	34	11	17
Kaist	KR	46	106	147	University of NEW MEXICO	USA	191	171	147
POHANG University of S&T	KR	5	14	17	UNC, Chapel Hill	USA	141	107	147
SEOUL National University	KR	261	252	147	Uni of NOTRE DAME du Lac	USA	32	34	17
DELFT University of Technology	NL	241	246	147	University of OREGON	USA	240	234	147
LEIDEN University	NL	21	10	17	University of PENNSYLVANIA	USA	64	40	147
MAASTRICHT University	NL	120	128	147	University of PITTSBURGH	USA	165	130	147
Radboud University NIJMEGEN	NL	126	113	147	University of ROCHESTER	USA	180	210	147
UTRECHT University	NL	115	115	147	University of SOUTH FLORIDA	USA	164	136	147
University of AMSTERDAM	NL	238	216	147	Uni of SOUTHERN CALIFORNIA	USA	102	75	147
University of GRONINGEN	NL	217	198	147	University of TENNESSEE	USA	221	200	147
University of TWENTE	NL	143	204	147	University of TEXAS At Austin	USA	78	49	147
WAGENINGEN University	NL	30	68	147	University of UTAH	USA	178	151	147
The University of AUCKLAND	NZ	265	259	147	University of VIRGINIA	USA	91	73	147
University of OTAGO	NZ	224	222	147	University of WASHINGTON	USA	85	48	147
NORWEGIAN University of S&T	NO	242	256	147	University of Wisconsin-Madison	USA	52	27	147
University of BERGEN	NO	123	154	147	VANDERBILT University	USA	229	231	147
University of OSLO	NO	266	260	267	WAKE FOREST University	USA	100	141	147
Nanyang Technological University	SG	245	232	147	WASHINGTON STATE University	USA	254	240	147
National University of Singapore	SG	99	71	147	WASHINGTON Uni In St. Louis	USA	45	44	17
University of CAPE TOWN	ZA	101	103	147	YALE University	USA	88	84	147
Autonomous Uni of BARCELONA	ES	264	254	147					
Autonomous Uni of MADRID	ES	55	38	147					
Uni De Santiago De Compostela	ES	144	118	147					
University of BARCELONA	ES	121	95	147					
University of VALENCIA	ES	157	135	147					

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Table 4: *Estimation results and Spearman correlations*

Estimation Results			
depvar: -Staff	<i>FE</i>	<i>SFA</i>	<i>True RE SFA</i>
Ugrad	-0.049 (0.040)	-0.1062*** 0.0141	-0.096*** 0.0072
Grad	-0.034 (0.029)	-0.0342*** 0.0124	-0.0363*** 0.0082
Cit	-0.821*** (0.033)	-0.8537*** 0.0174	-0.8333*** 0.0088
Ugrad_Ugrad	-0.040** (0.016)	-0.0317*** 0.0094	-0.0244*** 0.0049
Grad_Grad	-0.052 (0.033)	-0.0302** 0.0147	-0.0408*** 0.0077
Cit_Cit	0.002 (0.031)	0.0057 0.0143	0.0134 0.0096
Ugrad_Grad	0.018 (0.032)	0.0163 0.0177	0.0364*** 0.0107
Ugrad_Cit	-0.004 (0.034)	0.0295* 0.0167	0.0036 0.0105
Grad_Cit	0.055 (0.046)	0.0133 0.023	0.0215 0.0143
Year_2	-0.151*** (0.012)	-0.1473*** 0.0149	-0.1473*** 0.0115
Year_3	-0.152*** (0.012)	-0.1516*** 0.0135	-0.1528*** 0.0103
Constant	0.114 (0.071)	0.371*** 0.0186	
Lambda		2.3842	0.0006
Sigma(v)		0.2866	0.00001
Sigma(ν)		0.1202	0.1167
$\mu(\alpha_i)$			0.1296
$\sigma(\alpha_i)$			0.1574
N	720	720	720
SFA	No	Yes	Yes
University Effects	Yes	No	Yes
Spearman Correlations			
	<i>FE</i>	<i>SFA</i>	<i>True RE SFA</i>
<i>FE</i>	1		
<i>SFA</i>	0.9165	1	
<i>True RE SFA</i>	0.8519	0.8982	1
Peer Review	0.1043	0.2403**	0.1552**
Employer Review	-0.0178	0.022	-0.0409
Overall Quality	0.1318**	0.2126**	0.1348**

The top panel displays estimation results of a fixed effects (*FE*), a stochastic frontier (*SFA*) and a true random effects stochastic frontier (*True RE SFA*) estimator.

The bottom panel displays Spearman correlations of predicted efficiencies and quality measures (QS, 2010).

*, ** and *** denote significance levels of 10%, 5% and 1%.

Table 1 provides variable descriptions.

Lambda denotes the ratio of σ_ν and σ_v

μ_α and σ_α describe individual random effects.