The Global Production Frontier of Universities

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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.

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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

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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.\footnote{For 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.} The assumed production technology considers three outputs, namely
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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Staff</td>
<td>Employees (FTE)</td>
<td>1810.56</td>
<td>1077.97</td>
<td>85</td>
<td>6637</td>
</tr>
<tr>
<td>Ugrad</td>
<td>Undergraduate Students (FTE)</td>
<td>16022.98</td>
<td>12367.46</td>
<td>173</td>
<td>130227</td>
</tr>
<tr>
<td>Grad</td>
<td>Graduate Students (FTE)</td>
<td>5702.22</td>
<td>3860.37</td>
<td>372.3154</td>
<td>32283</td>
</tr>
<tr>
<td>Cit</td>
<td>Index of citations within 5 years</td>
<td>128953.9</td>
<td>83184.15</td>
<td>4576</td>
<td>458874</td>
</tr>
</tbody>
</table>

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 (\(\text{max}(\hat{\alpha}_i)\)) 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:

\[
-ln x_{it} = \sum_{m=1}^{3} \gamma_{m} lny_{mit} + \frac{1}{2} \sum_{m=1}^{3} \sum_{n=1}^{3} \gamma_{mn} lny_{mit}lny_{nit} + \delta_t + \alpha_i + \nu_{it}, \tag{1}
\]

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 \((y_{mit})\),

\(^2\)Hence, 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 \((\delta_t)\) account for differences across time. \(\nu_{it}\) refers to the traditional error term, i.e. follows a normal distribution with mean zero and variance \(\sigma^2\). \(\alpha_i\) denotes individual intercepts, i.e. university-specific dummy variables. Calculation of predicted technical efficiencies \((\hat{T}_E_i)\) follows

\[
\hat{T}_E_i = \exp(-\tilde{v}_i) = \exp(-(\max(\hat{\alpha}_i) - \hat{\alpha}_i))
\]

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:

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

The error term consists of two parts, i.e. \(\varepsilon_{it} = \nu_{it} + v_i\). As before, \(\nu_{it}\) refers to a normally distributed error term with mean zero and variance \(\sigma^2\). \(v_i\) 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

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

where \(\lambda = \frac{\sigma_v}{\sigma}\) and \(\sigma = \sqrt{\sigma_v^2 + \sigma^2}\). As above, the exponential of negative inefficiencies yields technical efficiency scores, i.e. \(\hat{T}_E_i = \exp(-\tilde{v}_i)\)

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, \(\alpha_i\), to formula 3 (Greene, 2005a,b). As the estimators’ name suggests, the
university-specific intercepts presumably follow a normal distribution with mean $\mu_\alpha$ and variance $\sigma_\alpha^2$. 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 $\varepsilon_{it}$ consists of two parts. $\nu_{it}$ refers to a normally distributed error term with mean zero and variance $\sigma_\nu^2$. Furthermore, the True RE SFA assumes that the second component, inefficiency, $\nu_{it}$, varies over time. Hence, the identifying distributional assumption concerning the inefficiency term becomes $\nu_{it} = |U_{it}|$, with $U_{it} \sim N(0, \sigma_\nu)$. 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**

<table>
<thead>
<tr>
<th></th>
<th>FE</th>
<th>SFA</th>
<th>True RE SFA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heterogeneity</td>
<td>0</td>
<td>0</td>
<td>$\alpha_i \sim N$</td>
</tr>
<tr>
<td>Inefficiency</td>
<td>$\max(\alpha_i) - \alpha_i$</td>
<td>$\nu_i =</td>
<td>U_i</td>
</tr>
</tbody>
</table>

**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
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

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

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.

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 \textit{FE} methodology but remains high throughout the top universities according to the \textit{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 \textit{FE} estimator but merely reaches the 13th rank based on the \textit{SFA} methodology. The volatility of estimates across methodologies remains high for both the middle and the bottom third of countries.

However, the \textit{FE} and \textit{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.\footnote{Similarly, 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 \textit{FE} and \textit{SFA} scores remains above 0.95.}

In order to provide a more thorough analysis of unobserved heterogeneity, table 4 further portrays the coefficient estimates of the \textit{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 \textit{FE} and \textit{SFA} methodologies. However, the estimated standard deviation of efficiency, $\sigma$, drops to merely 0.00001. Hence, the predicted efficiency scores barely vary, implying a negligible identification power of this estimator. The \textit{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 \textit{True RE SFA} yields efficiency esti-
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.
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 assess universities.

7 Tables

| Table 5: Ranks of predicted university efficiencies according to FE, SFA and True RE |
| University | FE | SFA | TRS |
| AUSTRALIAN National Uni | 146 | 162 | 147 |
| University of ADELAIDE, The | 182 | 182 | 147 |
| University of MELBOURNE | 232 | 195 | 147 |
| University of NEW SOUTH WALES | 147 | 122 | 147 |
| University of QUEENSLAND, | 201 | 179 | 147 |
| University of SYDNEY | 248 | 228 | 147 |
| Uni of WESTERN AUSTRALIA | 137 | 138 | 147 |
| MCI Management Center INNSBRUCK | AT | 31 | 37 | 17 |
| University of VIENNA | AT | 58 | 30 | 147 |
| Catholic University of LEUVEN | BE | 70 | 67 | 147 |
| Free University of Brussels(VUB) | BE | 134 | 175 | 147 |
| University of GHENT | BE | 272 | 271 | 267 |
| University of LIEGE | BE | 24 | 25 | 17 |
| Universite Catholique de LOUVAIN | BE | 41 | 52 | 147 |
| State University of CAMPINAS | BR | 187 | 194 | 147 |
| DALHOUSIE University | CA | 71 | 80 | 147 |
| LAVAL University | CA | 89 | 69 | 147 |
| McGill University | CA | 262 | 255 | 147 |
| McMaster University | CA | 17 | 8 | 17 |
| QUEEN'S University | CA | 160 | 156 | 147 |
| SIMON FRASER University | CA | 189 | 177 | 147 |
| The University of WESTERN ONTARIO | CA | 40 | 26 | 17 |
| University of ALBERTA | CA | 216 | 180 | 147 |
| University of BRITISH COLUMBIA | CA | 175 | 137 | 147 |
| University of CALGARY | CA | 42 | 28 | 147 |
| University of MANITOBA | CA | 223 | 208 | 147 |
| University of OTTAWA | CA | 114 | 94 | 147 |
| University of TORONTO | CA | 50 | 22 | 147 |
| University of VICTORIA | CA | 73 | 79 | 147 |
| University of WATERLOO | CA | 69 | 51 | 147 |
| University of WINNIPEG | CA | 241 | 230 | 147 |
| FUDAN University | CN | 283 | 244 | 147 |
| SHANDONG University | CN | 108 | 93 | 147 |
| University of China | CN | 145 | 183 | 147 |
| AARHUS University | DK | 142 | 140 | 147 |
| Technical Uni of DENMARK | DK | 113 | 158 | 147 |
| Uni of COPENHAGEN | DK | 271 | 269 | 147 |
| Uni of SOUTHERN DENMARK | DK | 249 | 265 | 147 |
| WAGeningen University | NL | 117 | 89 | 147 |
| University of HELSINKI | FI | 107 | 90 | 147 |
| University of TURKU | FI | 132 | 196 | 147 |
| Cambridge University | GB | 196 | 287 | 147 |
| Ecole Normale Superieure de LYON | FR | 2 | 129 | 147 |
| Ecole Normale Superieure, Paris | FR | 1 | 59 | 147 |
| Joseph Fourier Uni - GRENOBLE I | FR | 251 | 258 | 267 |
| Paris-Sud XI University | FR | 246 | 236 | 147 |
| Polytechic School (France) | FR | 49 | 203 | 147 |
| University MONTPELLIER II | FR | 207 | 242 | 147 |
| Uni Pierre and Marie Curie | FR | 267 | 261 | 267 |
| University of Strasbourg | FR | 72 | 91 | 147 |
| HUDDLED University | DE | 146 | 137 | 147 |
| Free University of BERLIN | DE | 82 | 55 | 147 |
| University of Erlangen-Nuernberg | DE | 150 | 143 | 147 |
| University of JENA | DE | 243 | 248 | 147 |
| Goethe Uni FRANKFURT | DE | 197 | 184 | 147 |
| HEIDELBERG University | DE | 220 | 213 | 147 |
| Heinrich Heine Uni of Dusseldorf | DE | 98 | 104 | 147 |
| Johannes Gutenberg Uni of MAINZ | DE | 20 | 16 | 17 |
| Ludwig Maximilian - Uni of MUNICH | DE | 153 | 127 | 147 |
| Ruhr University BOCHUM | DE | 256 | 244 | 147 |
| Saarland University | DE | 93 | 105 | 147 |
| ARIZONA STATE University | USA | 206 | 166 | 147 |
| BOSTON University | USA | 135 | 109 | 147 |
| BRANDIS University | USA | 19 | 65 | 17 |
| BROWN University | USA | 14 | 21 | 17 |
| CASE WESTERN RESERVE Uni | USA | 109 | 149 | 147 |
| COLORADO State University | USA | 57 | 45 | 147 |
| COLUMBIA University | USA | 90 | 62 | 147 |
| CORNELL University | USA | 62 | 43 | 147 |
| Caltech | USA | 3 | 13 | 17 |
| DARTMOUTH College | USA | 15 | 29 | 17 |
| DREXEL University | USA | 260 | 262 | 147 |
| DUKE University | USA | 86 | 72 | 147 |
| EMORY University | USA | 75 | 74 | 147 |
| FLORIDA State University | USA | 213 | 173 | 147 |

11
| University Name                                      | DE | 235 | 229 | 147 | DE | 233 | 206 | 147 | Technical University of Munich | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Cologne | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Athens | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Fribourg | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Paris | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Tubingen | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Konstanz | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Liége | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Münster | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Oldenburg | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Pennsylvania | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Poitiers | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Pretoria | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Regensburg | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Reykjavik | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Rome | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Uppsala | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Vietnam | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Würzburg | 235 | 229 | 147 | DE | 233 | 206 | 147 | National Technical University of Athens | 235 | 229 | 147 | DE | 233 | 206 | 147 | City University of Hong Kong | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of California, San Diego | 235 | 229 | 147 | DE | 233 | 206 | 147 | Indian Institute of Technology Delhi | 235 | 229 | 147 | DE | 233 | 206 | 147 | Indian Institute of Technology Kanpur | 235 | 229 | 147 | DE | 233 | 206 | 147 | Peking University | 235 | 229 | 147 | DE | 233 | 206 | 147 | Stanford University | 235 | 229 | 147 | DE | 233 | 206 | 147 | Sapienza University of Rome | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Arizona | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of California, Davis | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of California, Irvine | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of California, Riverside | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of California, San Diego | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Chicago | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Connecticut | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Colorado Boulder | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Delaware | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Florida | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Georgia | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Houston | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Illinois Urbana-Champaign | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Iowa | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Kansas | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Kentucky | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Maryland | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Miami | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Michigan | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Minnesota | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of New Mexico | 235 | 229 | 147 | DE | 233 | 206 | 147 | UNC Chapel Hill | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Oregon | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Pennsylvania | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Pittsburgh | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Rochester | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of South Florida | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Southern California | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Tennessee | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Texas at Austin | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Utah | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Virginia | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Washington | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Wisconsin-Madison | 235 | 229 | 147 | DE | 233 | 206 | 147 | Vanderbuilt University | 235 | 229 | 147 | DE | 233 | 206 | 147 | Wake Forest University | 235 | 229 | 147 | DE | 233 | 206 | 147 | Washington State University | 235 | 229 | 147 | DE | 233 | 206 | 147 | Washington University in St. Louis | 235 | 229 | 147 | DE | 233 | 206 | 147 | Yale University | 235 | 229 | 147 | DE | 233 | 206 | 147 | Autonomous University of Barcelona | 235 | 229 | 147 | DE | 233 | 206 | 147 | Autonomous University of Madrid | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Santiago de Compostela | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Barcelona | 235 | 229 | 147 | DE | 233 | 206 | 147 | University of Valencia | 235 | 229 | 147 | DE | 233 | 206 | 147 |
References

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Salerno, C., 2003. What we know about the efficiency of higher education institutions: the best evidence. University of Twente: CHEPS.


### Table 4: Estimation results and Spearman correlations

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<td>FE</td>
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<tr>
<td>Ugrad</td>
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<td></td>
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<tr>
<td>Grad</td>
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<tr>
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<tr>
<td>Cit</td>
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<tr>
<td>Constant</td>
<td>0.114</td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
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</table>

| Lambda   | 2.3842 | 0.0006 |
| Sigma(ε) | 0.2866 | 0.00001 |
| Sigma(σ) | 0.1202 | 0.1296 |
| μ(α)     | 0.1574 |
| σ(α)     | 0.0186 |

<table>
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<tbody>
<tr>
<td>FE</td>
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<tr>
<td>SFA</td>
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<table>
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<tr>
<th>Spearman Correlations</th>
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<tr>
<td>SFA</td>
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<tr>
<td>True RE SFA</td>
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<td>0.2126 **</td>
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<tr>
<td>0.1348 **</td>
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</table>

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 $\sigma_\varepsilon$ and $\sigma_\varepsilon$. $\mu_{\alpha}$ and $\sigma_{\alpha}$ describe individual random effects.