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Differences in cost structure and the evaluation of efficiency: the case of German universities

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A multiproduct cost function is estimated for German higher education institutions using a panel of data from recent years. The use of panel data allows a random parameter stochastic frontier model to be estimated, and this delivers new insights on the extent to which differences in costs between institutions producing similar vectors of outputs may be due to different cost structures, on the one hand, and efficiency, on the other. The approach used here therefore resembles in some respects the non-parametric methods of efficiency evaluation, since different loss functions attach to different universities. We report also on measures of average incremental cost of provision and on returns to scale and scope.

JEL classifications: C14; C23; C51; D20; I20

Keywords: stochastic frontier; random parameter models; costs; higher education

1. Introduction

Since the seminal work of Farrell (1957), the literature on efficiency evaluation has followed two directions. On the one hand, management scientists have pursued a linear programming approach – data envelopment analysis (DEA) – which involves the evaluation of input and output weights that in general differ across units of assessment (Charnes, Cooper, and Rhodes 1978). DEA is thus a non-parametric approach, and as such it does not lend itself naturally to the tools of statistical inference. By way of contrast, economists have pursued a statistical approach – stochastic frontier analysis (Aigner, Lovell, and Schmidt 1977) – which, based on regression, employs a decomposition of the residual into separate components designed to capture inefficiency and noise. This decomposition is effected by assuming that inefficiency and noise follow distinct distributional patterns. While stochastic frontier analysis has the appealing characteristic that the well-understood statistical tools become available, a less attractive property of this method is that it requires us to assume that the parameters of the cost (or production) function are identical across units of assessment.

Recent works by Tsionas (2002) and Greene (2005) allow the advantages of both methods to be realised within a single estimating methodology. Using panel data, a random parameters specification of a stochastic frontier cost (or production) function

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can be evaluated. This allows estimates of inefficiency to be obtained while at the same time relaxing the assumption that all units of assessment must face the same cost (or production) function. Indeed, it allows the parameters of this function to vary across units in much the same way as they do in a DEA. At the same time, the plethora of statistical tests that lend rigour to a regression type analysis remains available.

The main focus of the present paper will be the evaluation of efficiency in the universities of Germany. This group of institutions provides an ideal testing ground for the new methods of efficiency evaluation. Universities are not homogeneous – they vary in terms of their vintage, size, academic orientation, research intensity and so on. One might therefore expect no two universities to face the same cost function. Likewise, one might expect universities to vary in terms of their technical efficiency, not least because they are largely funded out of taxation and are therefore partially immune from the pressures of the market. Costs of institutions of higher education systems have recently been evaluated using the random parameter stochastic frontier approach outlined above (Johnes and Johnes 2009), but no such exercise has hitherto been attempted for the case of Germany. Universities in Germany are particularly interesting because of the recent introduction, both at national level and in each of the regions, of major reforms aimed in part at raising the efficiency of higher education.

The structure of this paper is as follows. The next section describes the data. This is followed by an exposition of the methods of analysis, and then by a section that discusses our results. A concluding section draws together our main findings and makes some suggestions for future research.

2. Data

The German higher education system comprises universities, which provide a comprehensive range of advanced academic teaching and research, and the Fachhochschulen, which have a more vocational orientation and are primarily teaching institutions that do not offer Ph.D. programmes. Although the correspondence is not exact, we shall henceforth refer to the latter as polytechnics. Unsurprisingly, a preliminary analysis of the data reveals that research activity in the polytechnics is limited. While research funding from third-party sources averages over €25 million per annum in the universities, the corresponding average in the polytechnics is a little over 1 million. We therefore focus the analysis exclusively on the universities, leaving a study of costs in the polytechnics as a topic for future research. All universities for which a full set of data is available are included, with the exception of the (specialist) Hannover medical school. The universities of Essen and Duisburg merged in 2003, and so are excluded from the sample analysed in this paper. Also excluded are a number of highly specialised small institutions in the fields of music and the arts, and also the group of private universities.

Data on German higher education institutions are provided from Fachserie 11 of the Federal Statistical Office. This provides data on education in general. They were processed by the ICE (Information, Controlling, Entscheidung) system at the Hochschul-Informations-System GmbH (HIS) based in Hannover. The data on student numbers cover the academic years 2002–03 through 2004–05, and the information about financial variables cover business years 2002 through 2004; unfortunately it is not possible to synchronise the data for academic and business years perfectly.

The variables used in the analysis are as follows. Total student numbers on bachelor and masters courses (or equivalent) are divided into two broad subject groups:

general science (including mathematics, natural sciences, veterinary medicine, agricultural, forest and nutritional sciences, and engineering) and all non-science subjects. We exclude medicine from the analysis on the ground that the provision of medical education in German universities severely distorts data on costs – in particular, nursing salaries and other miscellaneous expenditures disproportionately inflate the costs data for medical schools. Total numbers of doctoral students constitute another output variable.[1] Research activity is measured only by third-party funding (*Drittmittel*), a source of income to the universities that is primarily used for research – though a small proportion is awarded to the training of doctoral students and other activities. This measure of research is consistent with that used in most international studies of university costs, but it is not uncontentious. It could be argued that research funding represents an input, not an output. However, the measure has a number of advantages, and is increasingly being used as an indicator of research output specifically in the German context (see, for example, Warning 2007). First, it provides a contemporaneous measure of research activity, while publications-based measures are highly retrospective. Secondly, it provides a quality-adjusted measure of research output, in that it reflects, in some sense, a market value of the research that is being conducted. Thirdly, one might argue that, in a context where much applied research is conducted in the German language and therefore escapes bibliometric indices such as that of the Institute for Scientific Information (ISI), research income provides the only available credible measure of research activity. Fourthly, third-party funding is used by virtually all the Länder (henceforth referred to as regions) and by universities' own internal funding allocation mechanisms as the primary indicator of research activity (Jaeger et al. 2005). Finally, the dependent variable in our analysis is the sum of annual personnel and other current expenditures of institutions.[2]

The main source of funding for the core functions of teaching and research comes from the regional governments. In some early regression runs, we have included dummy variables for the regions, but since none of these proved to be significant we do not report these results here.

Descriptive statistics are reported in Table 1. Student numbers amount to, on average, a little under 10,000 in non-science areas, a little under 5000 in miscellaneous sciences and a little over 1000 in medicine. Somewhat less than 1000 doctoral students study at the typical university. Current expenditures amount to some 141 million at 2004 prices. The most prominent characteristic of the descriptive statistics is that, for each variable, the standard deviation is close to the mean. This indicates a considerable degree of heterogeneity across institutions, and in itself provides considerable justification for the approach adopted in this paper for the random parameter estimation of university cost functions.

Table 1. Descriptive statistics.

Variable	Mean	Standard deviation
Costs (€m, 2004 prices)	141.34	9.783
Non-science, taught students	9515.24	8050.12
Science, taught students	4900.20	4008.68
Doctoral students	844.16	894.90
Research income (€m, 2004 prices)	28.62	2.608

3. Methodology

A cost function is an envelope or boundary which describes the lowest cost at which it is possible to produce a given vector of outputs. Since it is an envelope, it is appropriate to use frontier methods in its empirical estimation; this is because a standard best-fit technique such as ordinary least squares would bias upward the estimation of costs on the envelope.

The standard approach to stochastic frontier estimation, based upon cross-section data, is due to Aigner, Lovell, and Schmidt (1977). In this model, the equation:

$$y_i = \alpha + \boldsymbol{\beta}'\mathbf{x}_i + v_i + u_i \tag{1}$$

is estimated using maximum likelihood, where v_i denotes normally distributed white noise error and u_i is a second residual term that is intended to capture heterogeneity across observations in the level of technical efficiency. This could in principle follow any non-normal distribution, though a common assumption – and one that we use here – is that it is half-normal.[3]

Following the contribution of Jondrow et al. (1982), it is possible to recover observation-specific estimates of the efficiency residual. These are given by:

$$\mathrm{E}[u_i|\varepsilon_i] = \sigma\lambda\{\phi(a_i)/[1-\Phi(a_i)] - a_i\}/(1+\lambda^2) \tag{2}$$

where $\varepsilon_i = v_i + u_i, \sigma = (\sigma_v^2 + \sigma_\mu^2)^{1/2}$, $\lambda = \sigma_u/\sigma_v$, $a_i = \pm\varepsilon_i\lambda/\sigma$, and $\phi(.)$ and $\Phi(.)$ are, respectively, the density and distribution of the standard normal.

When using panel data, Equation (1) is modified to:

$$y_{it} = \alpha_i + \boldsymbol{\beta}_i' \mathbf{x}_{it} + v_{it} + u_{it} \tag{3}$$

where $v_{it} \sim N\left[0,\sigma_v^2\right]$, $u_{it} = |U_{it}|$, $U_{it} \sim N\left[0,\sigma_{ui}^2\right]$ and v_{it} is independent of u_{it}. Equation (2) is likewise modified, for the panel data case, to:

$$\mathrm{E}[u_{it}|\varepsilon_{\mathrm{it}}] = \sigma\lambda\{\phi(a_{it})/[1-\Phi(a_{it})] - a_{it}\}/(1+\lambda^2) \tag{4}$$

It is then straightforward to obtain an indicator of technical efficiency that is defined over the unit interval[4] by dividing the predicted value of costs on the frontier by the predicted value of costs plus the one-sided residual.

To implement this specification, we model the $\boldsymbol{\beta}_i$ as random parameters. Greene (2005) defines the stochastic frontier as Equation (3) above, the inefficiency distribution as a half-normal with mean $\mu_i = \boldsymbol{\mu}'_i\mathbf{z}_i$ and standard deviation $\sigma_{ui} = \sigma_u\exp(\theta'_i\mathbf{h}_i)$; the parameter heterogeneity is modelled as follows:

$$\left.\begin{aligned}
(\alpha_i, \boldsymbol{\beta}_i) &= (\bar{\alpha}, \bar{\boldsymbol{\beta}}) + \Delta_{\alpha,\beta}\mathbf{q}_i + \boldsymbol{\Gamma}_{\alpha,\beta}\mathbf{w}_{\alpha,\beta_i} \\
\boldsymbol{\mu}_i &= \bar{\boldsymbol{\mu}} + \boldsymbol{\Delta}_\mu\mathbf{q}_i + \boldsymbol{\Gamma}_\mu\mathbf{w}_{\mu i} \\
\boldsymbol{\theta}_i &= \bar{\boldsymbol{\theta}} + \boldsymbol{\Delta}_\theta\mathbf{q}_i + \boldsymbol{\Gamma}_\theta\mathbf{w}_{\theta i}
\end{aligned}\right\} \tag{5}$$

Here, the random variation appears in the random parameters vector $\mathbf{w}_{ji}$ (where *i* is the index of producers and *j* refers to either the constant, the slope parameter or – in more general specifications of the model – the moments of the inefficiency distribution represented by $\boldsymbol{\mu}$ and $\boldsymbol{\theta}$); this vector is assumed to have mean vector zero and, in the case where parameters are assumed to be normally distributed, the covariance matrix equals the identity matrix. In the specification used in the present paper, $\mathbf{q}_i$ is a vector of ones; in more general specifications, it may be a matrix comprising variables that are hypothesised to influence the moments of the inefficiency distribution.

The unconditional log likelihood associated with this model includes within it a term containing an unclosed integral. This means that a simulated maximum likelihood,

$$\log\ \mathrm{L_S} = \sum_{i=1}^{N}\frac{1}{R}\sum_{r=1}^{R}\{\sum_{t=1}^{T}\ln \Phi\{[\mu_{ir} / (\sigma_{uir} / \sigma_v) \pm (y_{it} - \alpha_{ir} - \boldsymbol{\beta}'_{ir}\mathbf{x}_{it})(\sigma_{uir} / \sigma_v)] / \sqrt{\sigma_{uir}^2 + \sigma_v^2}\}$$
$$-\frac{1}{2}\{[\mu_i \pm (y_{it} - \alpha_{ir} - \boldsymbol{\beta}'_{ir}\ \mathbf{x}_{it})] / \sqrt{\sigma_{uir}^2 + \sigma_v^2}\}^2 + \ln\frac{1}{\sqrt{2\pi}} - \ln\Phi(\mu_i / \sigma_{uir})$$
$$-\ln\sqrt{\sigma_{uir}^2 + \sigma_v^2}\} \tag{6}$$

must be maximised to solve for the parameters of the model. This is achieved using Limdep.

Before we proceed to estimate empirical models of university costs, some further discussion is needed concerning the functional form with which we choose to work, and also about the various concepts of scale and scope economies that will inform the discussion in the sequel. The recent literature on costs in higher education institutions is built on the foundations provided in the literature on multiproduct cost function. This literature has highlighted the difficulty of choosing a cost function that makes sense in a multiproduct context. Baumol, Panzar, and Willig (1982) propose three suitable functional forms: the constant elasticity of substitution (CES), the quadratic and the hybrid translogs. The first of these is known to present some conceptual difficulties (Johnes 2004) and the last is demanding both in terms of data and its highly non-linear specification. We therefore choose to use the quadratic cost function. For university *k* in period *t*, costs are given by:

$$C_{kt} = \alpha_k + \sum\nolimits_i \beta_{ik} x_{ikt} + \sum\nolimits_i \sum\nolimits_j \chi_{ijk} x_{ikt} x_{jkt} + v_{it} + u_{it} \tag{7}$$

Alongside information about the costs and output vectors of a typical institution, this cost function can be used to provide a vast amount of information about the structure of costs, returns to scale and returns to scope in higher education. Following Baumol, Panzar, and Willig (1982), we define a number of concepts that will prove useful in the discussion that follows. To begin, where *n* distinct types of output are produced, we define the average incremental cost associated with the *i*th output, dropping unnecessary subscripts, as:

$$AIC_i = [C(x_1, x_2, \dots, x_i, \dots, x_n) - C(x_1, x_2, \dots, 0, \dots,\ x_n)] / x_i \tag{8}$$

In a single product firm, the ratio of average to marginal cost is often used as a measure of returns to scale. Where this ratio exceeds unity, economies of scale are observed; where it is less than one, there are diseconomies of scale. The concept of average incremental costs allows a similar ratio to be defined for the case of the multi-product organisation. For the *i*th output type, product-specific economies of scale are defined as:

$$S_i = AIC_i / (\partial C/\partial x_i) \tag{9}$$

An analogous statistic, measuring the effect of a proportional and simultaneous expansion of all output types, is a measure of the ray returns to scale, given by:

$$S = C(x_1, \ldots, x_n) / [x_1\partial C/\partial x_1 + \ldots + x_n\partial C/\partial x_n] \tag{10}$$

Lastly, we measure the returns to scope using the statistic:

$$\begin{aligned} S_c = {} & [C(0, x_2, x_3, \ldots, x_n) + C(x_1, 0, x_3, \ldots, x_n) + C(x_1, x_2, 0, \ldots, x_n) + \ldots + \\ & C(x_1, x_2, x_3, \ldots, 0) - C(x_1, x_2, x_3, \ldots, x_n)] / C(x_1, x_2, x_3, \ldots, x_n) \end{aligned} \tag{11}$$

If $S_c > 0$, economies of scope are said to be present; if, on the other hand, $S_c < 0$, then diseconomies of scope are observed. In many situations, we would not expect to observe diseconomies of scope, since firms faced by these in a competitive industry would divest. The (largely) public funding of universities renders the higher education sector a place where such competitive pressures are diminished, and so the possibility that the returns to scope could be diminishing needs to be considered.

4. Results

Armed with the above series of definitions of concepts, we are now able to proceed to a discussion of the results of the statistical analysis. We estimate two separate models of university costs. The first model is a random effects specification in which the weights attached to the various outputs are constrained to be constant across universities, but where the fixed cost term is allowed to vary across institutions. In the second model, we allow both the fixed cost term and the coefficient on research to vary across institutions. This is clearly a special case of a more general model in which all parameters are free to vary from one university to another; the more general model did not prove possible to estimate owing to a flat likelihood function, and this is why we report a relatively parsimonious variant of the random parameters model. Our results suggest that it is heterogeneity in fixed costs and in research that accounts for inter-institutional differences in cost structures.

The estimated cost equations are reported in Table 2. The first column reports the random effects specification, while the second reports the random parameters variant of our model. In both cases, these have been estimated using a stochastic frontier model in which efficiency is modelled as a half-normal residual, and where the random parameters follow a normal distribution. The results in this table are not easy to interpret, owing to the presence of a plethora of quadratic and interaction terms. We therefore proceed to discuss some more intuitive results that emerge from our analysis.

Table 3 reports some measures of interest that are specific to each institution. The first column reports the random effects that are produced in Model 1. These

Table 2. Regression results.[a]

Variable	Model 1: random effects	Model 2: random parameters
Non-science	0.0002	0.0002
	(1.63)	(2.06)
Science	0.0006	0.0006
	(2.57)	(2.55)
Ph.D.	0.0052	0.0052
	(4.50)	(4.52)
Research	2.5369	
	(5.37)	
Non-science[b]/10^7	–0.0560	–0.0560
	(1.08)	(1.05)
Science[b]/10^7	–0.3561	–0.3561
	(1.09)	(1.21)
Ph.D.[b]/10^7	–9.7254	–9.7254
	(2.90)	(2.57)
Research[b]	-1.2477×10^6	-1.2477×10^6
	(1.70)	(1.84)
Non-science × science /10^7	0.0914	0.0914
	(0.43)	(0.42)
Non-science × Ph.D. /10^7	0.9203	0.9203
	(1.31)	(1.40)
Non-science × research /10^7	–206.5650	–206.5649
	(0.80)	(0.80)
Science × Ph.D. /10^7	–2.0644	–2.0644
	(1.03)	(0.93)
Science × research /10^7	956.5820	956.5813
	(1.09)	(1.18)
Ph.D. × research /10^7	2913.9209	2913.9188
	(1.23)	(1.21)
Means for random parameters:		
Constant	–1.5490	–1.5490
	(3.39)	(3.40)
Research		2.5369
		(5.66)
Scale parameters for distributions of random parameters:[c]		
Constant	1.8358	1.8358
	(12.30)	(11.53)
Research		3.0368
		(18.47)
σ	3.0368	3.0368
	(10.41)	(10.75)
λ	1.8358	1.8358
	(4.50)	(3.61)

[a]The dependent variable is costs, measured in $\times 10^7$ in 2004 prices; [b]*t* statistics in parentheses; [c]Coefficients reported here are estimates of standard deviation of normal distribution of random parameters.

Table 3. Intercept shifts and slope shift on the research variable.

University	Intercept shift, Model 1	Intercept shift, Model 2	Slope shift, Model 2	Technical efficiency in 2004–05 using Model 2
U Freiburg i.Br.	–2.328	–1.602	2.173	0.908
U Heidelberg	–1.923	–1.805	2.338	0.892
U Hohenheim	–0.122	–1.345	3.320	0.838
U Karlsruhe	–2.453	–1.712	2.374	0.951
U Konstanz	–1.470	–1.479	2.426	0.856
U Mannheim	–1.320	–1.528	2.437	0.799
U Stuttgart	–2.537	–1.759	2.398	0.950
U Tübingen	–1.196	–1.564	2.543	0.926
U Ulm	–1.137	–1.461	2.769	0.805
U Augsburg	–1.745	–1.605	1.945	0.802
U Bamberg	–1.246	–1.462	2.644	0.588
U Bayreuth	–1.393	–1.560	2.533	0.817
U Erlangen-Nürnberg	–0.902	–1.645	2.630	0.932
U München	–1.550	–1.524	2.341	0.960
TU München	1.831	–1.552	2.994	0.953
U Passau	–1.457	–1.613	2.422	0.608
U Regensburg	–1.262	–1.556	2.536	0.872
U Würzburg	–3.348	–1.654	1.555	0.858
FU Berlin	–1.388	–1.584	2.414	0.965
TU Berlin	–0.318	–1.642	2.745	0.957
Humboldt-U Berlin	0.179	–1.473	2.908	0.957
U Potsdam	–3.579	–1.601	1.026	0.878
Europa-U Viadrina Frankfurt(Oder)	–1.934	–1.909	2.044	0.336
Brandenburgische TU Cottbus	–1.588	–1.502	2.435	0.751
U Bremen	–2.224	–1.475	2.303	0.936
U Hamburg	–0.276	–1.394	2.728	0.940
TU Hamburg-Harburg	–1.033	–1.396	2.849	0.743
TU Darmstadt	–2.645	–1.474	2.241	0.932
U Frankfurt a.M.	–4.298	–1.819	1.312	0.902
U Gießen	0.837	–1.437	3.777	0.928
U Kassel insg.	–0.982	–1.555	2.713	0.846
U Marburg	–0.960	–1.547	2.741	0.876
U Greifswald	–1.987	–1.651	1.893	0.802
U Rostock	–1.465	–1.598	2.452	0.853
TU Braunschweig	0.514	–1.416	3.095	0.934
TU Clausthal	–1.321	–1.520	2.676	0.749
U Göttingen	2.225	–0.762	3.415	0.910
U Hannover	–1.489	–1.465	2.436	0.914
Tierärztliche Hochschule Hannover	–0.800	–1.074	3.199	0.745
U Hildesheim	–0.846	–0.949	2.734	0.236
U Lüneburg insg.	–2.117	–2.100	1.872	0.511
U Oldenburg	0.303	–1.381	3.706	0.863

Table 3. (*Continued*).

University	Intercept shift, Model 1	Intercept shift, Model 2	Slope shift, Model 2	Technical efficiency in 2004–05 using Model 2
U Osnabrück	–0.920	–1.456	2.919	0.824
TH Aachen	–2.123	–1.289	2.430	0.972
U Bielefeld	–2.058	–1.594	2.158	0.851
U Bochum	0.202	–1.480	2.866	0.952
U Bonn	–0.105	–1.605	2.824	0.941
U Dortmund	–0.493	–1.468	2.844	0.879
U Düsseldorf	–1.128	–1.144	2.172	0.878
Fern-U Hagen	–1.683	–1.860	1.651	0.785
U Köln	–2.803	–1.494	1.686	0.936
Deutsche Sporthochschule Köln	–1.453	–1.569	2.404	0.601
U Münster	–1.156	–1.512	2.417	0.897
U Paderborn	–2.811	–1.698	1.816	0.882
U Siegen	–0.095	–1.133	3.702	0.844
U Wuppertal	–0.915	–1.491	2.830	0.829
TU Kaiserslautern	–2.694	–1.621	2.020	0.833
U Koblenz-Landau insg.	–2.038	–2.009	1.869	0.696
U Mainz insg.	–1.687	–1.572	2.196	0.931
U Trier	–2.547	–1.837	1.542	0.808
U des Saarlandes Saarbrücken	–3.272	–1.503	1.462	0.897
TU Chemnitz	–1.402	–1.599	2.535	0.837
TU Dresden	–4.633	–1.431	1.937	0.956
U Leipzig	–1.260	–1.511	2.422	0.919
U Halle insg.	–0.052	–1.289	3.105	0.873
U Magdeburg	–2.227	–1.493	1.920	0.856
U Kiel	–2.240	–1.359	2.022	0.881
TU Ilmenau	–4.154	–2.070	0.311	0.405
U Jena	–6.350	–2.163	0.070	0.527
Bauhaus-U Weimar	–2.839	–2.358	1.549	0.345
U der Bundeswehr München	2.192	1.078	5.866	0.734
Helmut-Schmidt-Universität Hamburg	1.622	0.770	5.411	0.585

Note: A number of small institutions are omitted from this table because, owing to their size, predicted costs are negative or only marginally positive. These institutions are the Hochschule für Politik München, Universität für Wirtschaft und Politik Hamburg, Hochschule Vechta, Internationale Hochschule Zittau, Universität Flensburg, Universität Erfurt and Universität Lübeck.

indicate systematic differences in costs across institutions that are not explained by differences in the explanatory variables. Such differences are due to unobserved heterogeneity – though as we shall argue later, this can be further decomposed. Some outliers are striking. There is a tendency for fixed costs to be lower in the new regions than in the old regions. However, we note that not all of these results are robust to the refinement that we introduce when considering the random parameters specification of Model 2.

In the second and third columns of the table, we report on the intercept shift (fixed cost effect) and the slope shift (the parameter on research) that are observed when the random parameters model is estimated.[5] There is now much less variation in fixed costs across institutions. What can be seen, though, is that technical universities (and the veterinary sciences only Tierärztliche Hochschule Hannover) tend to have somewhat higher fixed costs than others. There is, however, considerable variation across institutions in the costs attached to research activity. Personnel costs are relatively low in the new regions and relatively high in the old regions, and this has an impact on the variable costs associated with research. Hence, for example, the figure in the third column is high for institutions in the old Land of Lower Saxony such as Göttingen and Hildesheim, and low in the new Land of Thuringia for institutions like Jena and Ilmenau. The reason why the two universities of the German Bundeswehr (Universität der Bundeswehr München and Helmut-Schmidt-Universität Hamburg) have higher than average costs in all aspects is that these employ extra military personnel on top of the usual teaching personnel.[6]

It should be emphasised that, while in general the results obtained appear to accord with intuition, it is in the nature of a statistical exercise of this sort that outliers will exist. In particular, the estimates of the random parameters are just that – estimates – and to each of these attaches a confidence interval which may be quite large. Unfortunately, the short length of the panel precludes evaluation of these confidence intervals. This means that the results as they apply to any individual institution need to be treated with an appropriate degree of caution.

In the final column of the table, we report on efficiency differences across institutions. The efficiency scores reported here are obtained by calculating the ratio of predicted costs on the frontier to the predicted value of costs plus the one-sided residual. The results reveal notable efficiency differences across institutions, with small and specialised universities tending to be less efficient than others. For example, Hildesheim has a strong focus on language and cultural studies, and Bauhaus-Universität Weimar specialises in design and engineering; both are small institutions in terms of student numbers. On the other end of the scale, we find universities that enrol very high student numbers, tend to offer a broad subject range and are strong in research.

In Table 4, we report the average incremental costs associated with various outputs of the university system. Those attached to undergraduate provision in science and non-science subjects are very much in line with those reported in other studies (e.g. Johnes and Salas-Velasco 2007; Johnes and Johnes 2009). It is usual to find that science subjects are more costly to teach than other fields, and it is typically the case also that costs lie between 2000 and 10,000 per student year. The estimated costs associated with the delivery of doctoral education appear to be high in relation to those observed in other countries. This may be due in part to subject mix, since there is a high concentration of doctoral study in the sciences in Germany.

Table 4. Average incremental costs.

Output	Average incremental cost (€ per annum)
Non-science	2190
Science	6073
Ph.D.	50497

Table 5. Economies of scale and scope.

Product-specific returns to scale:	
Non-science	1.32
Science	1.40
Ph.D.	1.19
Research	1.15
Ray returns to scale	0.98
Returns to scope	–0.58

We report measures of scale and scope economies in Table 5. Again these are based on the random parameters model, using mean values of outputs. The results indicate that product-specific economies of scale are ubiquitous. Ray economies of scale are, however, exhausted, because the returns to scope are negative. In a nutshell, these results suggest that economies could be realised by an increased concentration of activity (i.e. a greater degree of specialisation) amongst German universities.

5. Conclusions

The first generation of multiproduct cost function estimates for universities is exemplified by Cohn, Rhine, and Santos (1989). These studies used OLS methods to estimate a cost function which satisfies the desiderata of Baumol, Panzar, and Willig (1982); the function ensures that sensible estimates of costs are obtained when a zero quantity of some output types is produced, and it does not presuppose the existence or otherwise of economies of scale and scope. The second generation refined this approach by using stochastic frontier methods. The present paper is a contribution to a new, third generation of studies which is characterised by a random parameters variant of the stochastic frontier model. This allows efficiency differences between universities to be distinguished from differences in the cost structures from one university to another. As such, the method has much in common with non-parametric approaches to efficiency evaluation such as DEA, but it retains the advantage that the tools of statistical inference can be applied.

This approach raises some conceptual issues that warrant some attention. One university may have higher fixed costs than another because, for example, it has relatively old buildings that require costly maintenance. Or a university may have unusually high costs of teaching because it employs unusually resource-intensive (but arguably effective) methods of tuition. Whether these higher costs are in some sense legitimate is, however, a judgement call. One could argue that the first university should move into less costly premises, and that the second should reform its teaching style. Alternatively one could argue that ancient buildings have heritage value, and that small group teaching fosters deep learning. The boundary between legitimately high costs and inefficiency is therefore moot. This caveat should be borne in mind when assessing the findings reported in this paper. Likewise, the reader should bear in mind the short length of the panel.

The results reported in the paper are broadly in line with intuition. It is more costly to provide science than other subjects. Postgraduate (doctoral) tuition costs more than lower levels of higher education – though the extent of this gap is somewhat surprising. There remain unexhausted product-specific economies of scale, but returns to scope are negative, suggesting that greater concentration of activities would yield economic gains. German institutions would appear to be efficient, but there are marked differences in cost structures between universities. These differences are associated with both fixed costs and the costs of producing research.

Notes

1. Unfortunately we do not have data on doctoral student numbers by subject area. One might speculate that doctorates in science are more costly than in other areas of academic endeavour, but our data do not allow us to confirm (or refute) this.
2. Since this is a measure of *expenditure*, not of income, we do not consider it appropriate to deduct from this measure the value of third-party funding.
3. A rarely noted conceptual issue arises here. Since the efficiency of an organisation is, in some sense, made up of the sum of efficiencies of the individuals that make up that organisation, one might expect, by the central limit theorem, to find that the distribution of efficiencies across organisations is normal. This violates a key assumption of the stochastic frontier approach. However, we note that the evidence from numerous DEA studies – which impose no prior distribution on organisational efficiency – does not suggest that inefficiency is normally distributed in practice, and we regard this as sufficient evidence to support the use of the, now standard, statistical frontier methods. Moreover, the significance of the σ and λ terms reported in Table 2 suggests that our approach is appropriate.
4. Except for rare cases where the predicted costs, and hence also the efficiency measure, are negative.
5. We estimate a random parameter on the third-party funding variable only. We experimented with specifications in which parameters on the other explanatory variables were allowed to be random, but the maximum likelihood estimates that resulted from such specifications did not point to any inter-institutional variation in the parameters.
6. Re-estimating the random parameter model without these two universities does not substantively affect the results.

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