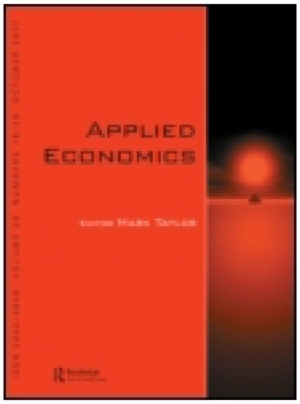

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Heterogeneity and the evaluation of efficiency: the case of Italian universities

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A random parameters stochastic frontier model is applied to Italian data in order to evaluate the cost function and efficiency of higher education institutions. The method yields useful information about inter-institutional variation in cost structure and technical efficiency. Returns to scale and scope are evaluated for the typical university, and it is found that these returns are almost ubiquitously decreasing, a finding with clear policy implications.

I. Introduction

The evaluation of efficiency has been a topic of interest to economists and management scientists alike for half a century. The early work of Farrell (1957) has been developed both along statistical lines, giving rise to stochastic frontier models (Aigner *et al.*, 1977) and along nonparametric lines, using methods grounded in linear programming, giving rise to the method of data envelopment analysis (DEA) pioneered by Charnes *et al.* (1978). These methods have both been very widely applied in the empirical literature (see, for example, Johnes, 1998). Yet both approaches suffer from a number of drawbacks.

In stochastic frontier analysis, the researcher imposes a functional form on the mapping between a set of explanatory variables and the dependent variable. The coefficients estimated by the application of the method are *assumed* to be constant across observations – that is, it is a parametric method. The set of residuals that attach to the observations used in estimating the model are then decomposed into two components – the first is a nonnormal component that is supposed to reflect efficiency, and the second is a normal component analogous to the residuals that are yielded by any other statistical regression-type analysis. The presence of these latter residuals allows the tools of statistical inference to be employed, and this is often considered to be a considerable advantage of this technique. The benefit of statistical inference is therefore bought at the cost of employing a parametric method.

By way of contrast, DEA is a nonparametric method. It uses linear programming methods to assign an observation-specific set of weights to outputs and inputs in such a way that the ratio of weighted output to weighted input is maximized for each observation (subject to certain constraints). This ratio can then be used as a measure of efficiency. Note that each observation is attached to its own set of 'coefficients'. This approach is very appealing in that it recognizes that different observations are just that – different. In a context where the observations are producers, it allows the producers in the data set to have different objectives to one another. A disadvantage of this approach is that by allowing

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each observation to be associated with a different set of weights, there is no scope for (regression-type normal) residuals to be evaluated, and hence statistical inference cannot be used.

Our aim in the present article is to address these drawbacks by application of a recently developed extension to the stochastic frontier method. We draw on the work of Tsionas (2002) and Greene (2005), and on a panel data set, to estimate a stochastic frontier model of costs in Italian universities where parameters are allowed to vary across institutions but where the institution-specific parameters are constrained to be constant over time. Such a random parameters approach has the benefit of DEA in that it allows each institution to have a distinct cost function, but has also the benefit of the stochastic frontier method in that it retains the toolkit of statistical inference.

Higher education is an arena where both the evaluation of efficiency and the estimation of cost functions are commonplace. There are several reasons for this. First, there has been a clamour for performance indicators in higher education in many countries (Johnes and Taylor, 1990). Second, partly because of this, data are publicly available on costs and outputs of higher education institutions. Third, the explicitly multi-product character of universities, dealing as they do in teaching and research, renders them an ideal subject for analyses of costs in a production context characterized by complexity (Baumol *et al*., 1982). Despite this, it is only recently that empirical studies of the university sector has used frontier methods to estimate models that simultaneously evaluate costs and provide measures of institutional efficiency (Johnes, 1997; Izadi *et al*., 2002; Stevens, 2005). Indeed there are no published studies that use random parameter methods in this context.[1]

The literature on Italian universities is sparse. Agasisti and Dal Bianco (2006a, b) have conducted DEA and stochastic frontier analyses of higher education in Italy and find a great deal of diversity within the sector. In particular, there are regional effects, with institutions in the north outperforming those in the south. Overall, however, the mean level of efficiency (relative to the frontier) is high. However, there are no studies of the Italian context that fully exploit the potential of panel data in this context, and our understanding of costs and efficiency in Italian universities remains very limited.

The remainder of the article is structured as follows. The next section provides some brief institutional information about the Italian university system. Section III discusses the methodology to be used. Section IV concerns the data. The main results are reported and discussed in the following section, and the final section draws together our findings and presents conclusions.

II. Italian Universities

The Italian university system has traditionally been strongly regulated by central government. This has been particularly pronounced in the sphere of managerial issues and finance. It extends also to the pattern of teaching provision across universities.

Since the mid-90s, however, there has been a process of reform, the objective of which has been to restore a high degree of autonomy to the institutions. Until 1993, universities were allocated budgets by government which they had to adhere to line by line. Since 1993, instead, they have been allocated a total budget but have had full autonomy to determine how that budget should be spent. In 1999, universities were given the autonomy to determine, for the most part, the content of courses.

This increased autonomy has encouraged universities to pay heed to the efficiency of their operations, the definition of their own priorities, the creation of brand, and so on. Sources of university funding are now much more hetereogeneous than in the past, with about 30% of income now coming from private sources.

In spite of this high degree of autonomy, Italian institutions remain broadly similar in their mission and status. The system is characterized by the absence of a (contemporary or historic) binary divide between, say, academically and vocationally oriented institutions. All institutions have university status, and the vast majority of them are comprehensive in terms of their subject coverage.

The 1999 teaching reform made inroads into fixing a chronic problem of Italian higher education – that is the tendency for many students to take a long time to complete their studies. While each programme of study has a notional time to completion, the culture has been one in which large numbers of students take longer than this to graduate. Those students who have been enrolled on their programmes for less than the notional time to completion are referred to as ‘regular’ students; those who graduate within the notional time are referred to as ‘regular’ graduates. The proportion of all students (graduates) who may be classed as regular students

[1] Although an unpublished study by Johnes and Johnes (2006) applies this method to English institutions of higher education.

(graduates) is low. For instance, in 2001–2002, regular students made up under 50% of the student body, and regular graduates made up less than 10% of all graduates.

In response to this problem, and to pressures operating at European level through the Bologna accord, the authorities have attempted to shorten the time to qualification. Until 2001–2002, all students studied for a *Laurea* degree, equivalent to a masters. Since then a bachelors/masters structure has been introduced. The shorter time to qualification is intended to reduce the incidence of drop-out and of part-time study, and hence to accelerate students' progress through higher education. While the extent to which this reform will succeed in reducing times to completion, is nuclear the early signs are encouraging – by 2003–2004 the proportions of students and graduates deemed 'regular' had already risen to 55% and 15%, respectively.

III. Methodology

There are three aspects of methodology that need to be discussed. First we consider the frontier estimator. Second, consideration is given to the functional form of the cost equation. Third, we briefly review some concepts that are of relevance in the context of multi-product organizations.

The simultaneous evaluation of costs and efficiency is natural. Cost functions represent an envelope or boundary which describes the lowest cost at which it is possible to produce a given vector of outputs. It follows that a frontier method of estimation is required to identify such an envelope. Frontier methods allow, as a byproduct, the evaluation of technical efficiency.

The simple stochastic cost frontier estimator, based upon cross-section data, is due to Aigner *et al.* (1977). In this model, maximum likelihood methods are used to estimate the equation

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

where v_i denotes a normally distributed residual (often attributed to measurement error) and u_i is a second residual term that is supposed to capture efficiency differences across observations. This could in principle follow any nonnormal distribution, so that it can be separated out from the other residual term, but a common assumption (and one that we follow in this article) is that it follows a half-normal distribution.

While early exponents of stochastic frontier methods were primarily interested in locating the cost envelope correctly, it soon became clear that useful information could be yielded by the method if the two residual components could be separated out at the level of the individual observation. This allows observation-specific estimates of technical efficiency, not unlike those yielded by DEA, to be obtained. Jondrow *et al.* (1982) show that such estimates are given by

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

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

In the present article we use panel data, and so (1) needs to be modified so that

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

Here the $\boldsymbol{\beta}_i$ are modelled as random parameters, and we assume that these follow the normal distribution. Greene (2005) summarizes the problem by defining the stochastic frontier as (3) above, the inefficiency distribution as a half-normal with mean $\mu_i = \boldsymbol{\mu}'_i\mathbf{z}_i$ and SD $\sigma_{ui} = \sigma_u\exp(\theta'_i\mathbf{h}_i)$. The parameter heterogeneity can then be modelled as follows:

$$\left.\begin{aligned}
(\alpha_i, \boldsymbol{\beta}_i) &= (\bar{\alpha}, \bar{\boldsymbol{\beta}}) + \Delta_{\alpha,\beta}\,\mathbf{q}_i + \boldsymbol{\Gamma}_{\alpha,\boldsymbol{\beta}}\mathbf{w}_{\alpha,\boldsymbol{\beta}_i}\\
\boldsymbol{\mu}_i &= \bar{\boldsymbol{\mu}} + \boldsymbol{\Delta}_{\boldsymbol{\mu}}\mathbf{q}_i + \boldsymbol{\Gamma}_{\boldsymbol{\mu}}\mathbf{w}_{\boldsymbol{\theta}i}\\
\boldsymbol{\theta}_i &= \bar{\boldsymbol{\theta}} + \boldsymbol{\Delta}_{\boldsymbol{\theta}}\mathbf{q}_i + \boldsymbol{\Gamma}_{\boldsymbol{\theta}}\mathbf{w}_{\boldsymbol{\theta}_i}
\end{aligned}\right\} \tag{4}$$

Here the random variation appears in the random 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 adopted here where parameters are assumed to be normally distributed, the covariance matrix equals the identity matrix. The vector $\mathbf{q}_i$ denotes a set of variables deemed to impact upon the distribution of random parameters (in the sequel assumed to be an empty set). Hence each of the institution-specific coefficient vector, the institution-specific mean of the asymmetric residual and the institution-specific shifter on the SD of the asymmetric residual is defined by its mean value plus some multiple of the random vector $\mathbf{w}$, plus a multiple of the arguments that influence the random parameters, $\mathbf{q}$.

A question that must be resolved before proceeding to estimation is whether or not we constrain the efficiency term, u, to be constant over time. In the results reported in the sequel, we do not impose this constraint; in the context of a short panel such as ours, this is unlikely to be a severe limitation.

The model is solved by simulated maximum likelihood; simpler techniques are precluded by the existence of an unclosed integral in the unconditional log likelihood (Tsionas, 2002; Greene, 2005). It is solved using Limdep, and the speed of solution has been increased by using Halton (1960) sequences of quasi-random draws to generate cheaply the equivalent of a large number of random simulations in evaluating the unclosed integral.

We now turn to consider the functional form of the cost equation. Baumol *et al*. (1982) provide a set of three desiderata that should be met by any cost function that is used to model a multi-product organization. Such functions should be 'proper' cost functions, in the sense that they should be nonnegative, nondecreasing, concave and (where input prices appear as explanatory variables[2]) linearly homogenous in input prices. Cost functions should predict sensible values of costs for firms that produce zero levels of some outputs – this rules out candidates such as the translog cost function. They should also not prejudge the presence or absence of economies of scale or scope – this rules out linear functions.[3]

Based on these desiderata, Baumol *et al*. (1982) suggest three candidate forms for a multiproduct cost function. These are the CES, the quadratic and the hybrid translog. Of these, the first and last are highly nonlinear and do not lend themselves to straightforward estimation using frontier techniques.[4] We therefore employ the quadratic cost function. Abstracting for the moment from residual terms, this is given by

$$C = a_0 + \sum_i b_i y_i + \left(\frac{1}{2}\right) \sum_i \sum_j c_{ij} y_i y_j \tag{5}$$

where y_i denotes the output of type i. The presence in this equation of quadratic terms allows, but does not impose, economies or diseconomies of scale; the function also allows interaction between the various outputs being produced to impact upon costs through synergy (economy of scope) effects. The quadratic cost function has been used in numerous applications including the earliest and most recent studies of university costs (Cohn *et al*., 1989; Johnes, 1997; Johnes *et al*., 2005).

The final aspect of methodology that we need to consider at this stage concerns a variety of cost concepts that relate to multi-product production. Baumol *et al*. (1982) define the average incremental cost associated with product k as

$$\mathrm{AIC}(y_k) = \frac{[C(y_N) - C(y_{N-k})]}{y_k} \tag{6}$$

where $C(y_N)$ is the cost of producing the outturn output vector, and $C(y_{N-k})$ is the cost associated with producing the outturn values of all outputs other than the kth output, and where the output of type k is zero.

Product-specific economies of scale associated with the kth output can then be defined as

$$S_k(y) = \frac{AIC(y_k)}{C_k(y)} \tag{7}$$

where $C_k(y)$ is the marginal cost associated with the kth output. This definition is therefore analogous to the ratio of average to marginal costs that is often used as a measure of scale economies in single product contexts. A value of $S_k(y)$ that exceeds unity reflects product specific returns to scale that are increasing, and vice versa.

Ray economies of scale are defined as

$$S_R = \frac{C(y)}{\sum_k y_k C_k(y)} \tag{8}$$

A value of S_R exceeding unity indicates that a simultaneous proportional increase of in the production of all output types results in economies of scale, while a value less than one indicates decreasing returns to scale.

Global economies of scope are calculated using the formula

$$S_G = \frac{\left[\sum_k C(y_k) - C(y)\right]}{C(y)} \tag{9}$$

where $C(y_k)$ is the cost of producing only the outturn value of kth output, with zero output of all other types. This formula therefore compares, in the numerator, the cost of producing the outturn output vector in a single institution with that of

[2] They need not be. In highly regulated contexts in particular, input prices may be constant across observations. It has therefore been unusual in the empirical literature on higher education costs to include input prices in the specification of estimated models.

[3] Johnes (2004) has identified a fourth desideratum – that estimated cost functions should not imply that the sustainable configuration of an industry is one in which firms are not multi-product. This desideratum rules out some empirically estimated equations which have a functional form that passes the other desiderata.

[4] Izadi *et al*. (2002) have estimated a frontier variant of the CES model using cross-section data. The estimation of an analogous model using random parameters would present a formidable computational task, though.

producing the same output in several different, single-product, institutions. If S_G is positive, then it is cheaper to produce jointly than not, and so economies of scope are said to exist. Conversely, $S_G < 0$ implies diseconomies of scope.

Product-specific returns to scope associated with output of type k can analogously be defined as

$$SC_i = \frac{[C(y_k) + C(y_{N-k}) - C(y)]}{C(y)} \tag{10}$$

IV. Data

The clamour for performance indicators in Italy has led to the creation of the *Comitato Nazionale per la Valutazione del Sistema Universitario* (CNVSU – the National Committee for the Evaluation of the University Sector). This committee makes publicly available a wide variety of data concerning the university system in Italy, and our data all come from the CNVSU website.

They refer to public Italian universities over the period 2001–2002 through 2003–2004. One university (Napoli Parthenope) is excluded from our analysis because of incomplete data. We also exclude all 14 private sector universities, owing to the absence of comparable data on financial variables. This leaves us with a sample of 57 universities, each of which yields data over the three year period, so we have a total of 171 observations.

All financial data have been inflated to 2003 values using RPI data from the National Institute of Statistics (http://www.istat.it). The inflators are, respectively for the first two years of the study, 1.0495 and 1.0246. Financial data refer to the calendar year, while data on student numbers refer to the academic year: these data are matched by attaching the financial data for the calendar year in which the academic year begins to the student data from that academic year.

Costs are defined as current expenditure during the year, and are measured in thousands of euros. Capital costs and depreciation are not included. While the definition of costs is imposed upon us by data limitations, we note that there is in any event a strong case for focusing on current costs only, since the lumpy nature of capital expenditures could otherwise lead to noise in the dependent variable. Outputs include measures of student numbers and of research activity, with some disaggregation into broad subject area. Hence we use measures of: the number of students on undergraduate courses in sciences (SC); the number of students on other undergraduate courses, such as the arts, humanities, and social sciences (HUM); the total number of research students (PHD); and, as a measure of research activity, the value of grants for external research and consultancy (RES). We also include in our analysis a binary variable (MEDIC) which indicates whether or not an institution has a medical school. Medical degrees in Italy are longer than other degrees, with a standard duration of 6 years.

There are aspects of these variables that warrant discussion. In contrast to studies conducted elsewhere, data on student load refer to the total number of students, rather than to full-time equivalents, or to numbers of graduates. The latter measure might be deemed desirable if the primary concern is the output of universities, and if one is inclined to a credentialist view of education. However, it is the number of students being educated that influences costs, and a human capital view suggests that there is tangible output embodied in those students who learn while at university but who fail to complete their course. Unfortunately the Italian data do not allow a distinction to be made between full-time and part-time students, and so information about full-time equivalence is unavailable.[5] The use of a binary variable to indicate the presence of a medical school is clearly somewhat ad hoc; we know from work done in the UK (Johnes *et al.*, 2005) that the costs attached to medical studies are far higher than those associated with other scientific fields. With a relatively small dataset in the case of Italy, it has not proved possible to identify medicine as a separate subject area, not least because the inclusion of a full set of quadratic and interaction effects would entail too great a loss of degrees of freedom.

Perhaps the most contentious variable is our measure of research. It can be argued that grants represent an input into the research process, and should not therefore be used as a measure of research output (Johnes and Johnes, 1993). However, in the absence of research assessment exercise data for Italy, this offers the best signal we have of the research productivity of universities. Grants represent a measure of the market value of research done, and so provides a neat conflation of the quantity and quality of research effort. They also provide a measure of research output that is less retrospective than bibliometric analyses. In countries, such as

[5] While many nonregular students may be studying part-time, the same is true of many regular students, and there appears to be no way of disentangling information about mode of study from the information that is available.

the UK, where both research grant and research assessment measures are available, the two measures are highly correlated. We therefore believe that, while our measure of research output could probably be improved upon, it is adequate for the task.

Descriptive statistics for all variables used in this study, over the three year period, appear in Table 1. Student numbers are high in relation to those observed at universities in many other countries. This is in large measure due to the long programmes of study undertaken by students; indeed the typical programme of study in Italian universities has traditionally led to a *Laurea*, equivalent to a masters degree. The Bologna process has led to the recent introduction of separate bachelor and masters level programmes, but the norm is still for students to remain in university for five or more years. Despite the high number of students, costs are relatively low, this reflecting the mass education nature of the Italian higher education system – where students are typically taught in very large groups. A further notable feature of the data is the magnitude of the SD which are high in relation to the corresponding mean. This is suggestive of a great deal of diversity amongst the Italian universities.

Table 1. Descriptive statistics

	costs (0.000€)	SC	HUM	RES (0.000€)	PHD
Mean	106671.63	8742.19	16626.37	8921.40	529.56
Median	72806.50	5862.00	12874.00	3210.94	360.00
St.Dev.	98455.19	9230.27	15660.08	11443.60	514.63
Minimum	6302.63	0.00	0.00	0.00	0.00
Maximum	504320.00	39525	85780	48865.41	2520

Note: all the financial data are reported in 000€, 2003 prices.

V. Results

In Table 2, we report the results of two variants of the model. In the first column, we report coefficients for a random effects model, that is one where there is only one random parameter, namely the constant. In the second column, we report a fuller random parameters specification, where the constant and the linear terms in SC, HUM, RES and PHD are all associated with parameters that are allowed to vary across institutions. In all cases the random parameters are constrained to follow a normal distribution. We do not report results for a fixed effects model; experience shows that with short panels such as the one used in the present study there may be collinearity between the fixed effects and the variables in the vector of explanatory variables and that this makes the results of fixed effects estimation unreliable.

The first thing to note from the table is the high (and highly significant) coefficient attached to the MEDIC variable. Clearly Italy is no exception to the rule that medical schools add a lot to a university's costs. The remaining coefficients are rather more difficult to interpret owing to the nonlinear terms included in the equation; we shall come to discuss the implications for costs of the remaining outputs in due course.

A glance at the results in the right hand column of the table (and in particular at the random parameters) indicates that there is considerable variation across universities in the impact that undergraduate students (in all subjects, but especially in nonscience fields) and research have on costs. This is investigated further in Table 3, where we report the institution-specific shifter for each of the linear output terms. Nonscience students clearly each add much more to costs in institutions like Genova and Pavia than they do in universities such as Napoli – Federico II and (possibly an outlier) Foggia.[6] The former institutions face considerable competition both from each other and from the science-oriented *politecnici*, which are primarily located in the north. This would appear to have led to a game in which institutions compete with each other to provide students with the best facilities, thereby raising costs. Likewise, research adds more to costs in Torino and Siena than in Catania or Salerno. Geography again may provide an explanation for this: attracting government funding and consultancy may be both easier and cheaper (and so more commonly achieved) for universities located in the north (where the private sector is strong) and the central region than in the south.

In the final column of Table 3, we report on the technical efficiency of each institution, calculated using the full specification of the random parameters model by finding the ratio of the predicted value of costs to the sum of the predicted value of costs and the value of the u component of the residual. The reported efficiencies relate to the academic year 2002–2003. In general the estimated efficiencies are

[6] Foggia is a small university, recently founded in a relatively poor area of the country. At this stage in its development, it has characteristics that could set it apart from other institutions.

Table 2. Regression results

Variables	RE (*)		RPM(*)	
Constant	−14292.745	(−3.977)	−8237.953	(−5.074)
SC	3.475	(4.247)	3.100	(10.772)
HUM	1.172	(2.245)	2.991	(15.168)
RES	−0.200	(−0.431)	0.629	(2.668)
PHD	39.692	(1.741)	23.014	(2.959)
SC*SC	0.589	(0.971)	0.412	(2.867)
HUM*HUM	−0.142	(−0.588)	−0.408	(−3.647)
RES*RES	0.456	(3.364)	0.096	(1.316)
PHD*PHD	664.013	2.403	382.736	(3.545)
SS*HUM	0.334	(0.799)	1.031	(5.495)
SC*RES	0.758	(1.112)	0.503	(2.183)
SC*PHD	−53.182	(−2.572)	−30.511	(−3.696)
HUM*RES	0.132	(0.476)	−0.085	(−0.738)
HUM*PHD	7.619	−0.697	4.601	(0.770)
RES*PHD	−21.103	(−1.366)	−12.055	(−2.851)
MEDIC	23182.772	−7.694	13361.926	(7.806)
Random Parameters (**) SD of:				
Constant			7.39*E06	(0.000)
SC			0.142	(2.183)
HUM			1.161	(20.850)
RES			0.785	(11.098)
PHD			0.042	(0.036)
λ	3.248	(3.281)	3.248	(3.020)
σ	26730.372	(15.397)	15406.666	(13.319)
log likelihood	−1902.670		−1861.962	

Notes: (*) t-statistics in parentheses, the coefficient reported for each random parameter is the mean; (**) we report estimates of SD of normal distribution of random parameters.

high, with an average efficiency score of over 81%.[7] There are, however, some outliers. Some of these, including Bergamo, Cantanzaro, Foggia, and Sannio, have relatively low values of measured efficiency, but are relatively cheap providers of nonscience undergraduate education. The opposite is true in the case of some other institutions, most notably Genova. It is possible that, for some institutions, the statistical method being used finds it difficult to distinguish between efficiency and cost structures; this is a problem of observational equivalence that is somewhat akin to multicollinearity. In general, though, the results are plausible and suggest that the random parameters approach to frontier estimation can be extremely instructive in identifying inter-institutional differences in both cost structures and efficiency. For purposes of comparison, the efficiencies obtained by a standard random effects stochastic frontier are also reported in the table (column 1); these have more dispersion than the efficiencies that emerge from the random parameter specification, not least because in the random effects model there is more limited scope for cost differences to be due to inter-institutional heterogeneity. The correlation between the efficiencies obtained from random effects estimation and those yielded by the random parameters estimation is quite high; the value of r is 0.69 and the Spearman's rank correlation is 0.82

It is necessary to note at this stage an important caveat about the random parameter results and the efficiency estimates that arise from this analysis. There are institutions (such as Genova) that score highly for efficiency in the random parameter model, but where the costs of producing one of the outputs (in this case nonscience undergraduates) is unusually high. Without knowing the reason for this, the high efficiency score of the institution in question needs to be regarded with caution. If the cost of producing nonscience undergraduates is high for good reason, then the high efficiency

[7] This compares with figures for England, where Johnes and Johnes (2006) provide a mean efficiency score of about 75%. It should, however, be borne in mind that the efficiencies in each country study are defined in relation to the country-specific frontier.

Table 3. Efficiencies and slope shifts

University	RE_ efficiency	RPM - SC shift	RPM - HUM shift	RPM - RES shift	RPM - PHD shift	RPM_ efficiency
ANCONA	0.747	3.098	2.799	0.472	23.006	0.824
BARI	0.945	3.092	2.842	0.326	23.007	0.942
BARI – Politecnico	0.818	3.019	2.921	0.277	23.016	0.879
BASILICATA	0.381	3.118	3.147	0.817	23.013	0.718
BERGAMO	0.169	3.076	1.805	0.624	23.013	0.635
BOLOGNA	0.977	3.206	2.806	0.247	23.001	0.976
BRESCIA	0.447	3.096	2.966	0.673	23.018	0.726
CAGLIARI	0.622	3.106	3.034	0.551	23.024	0.937
CALABRIA	0.767	3.105	1.737	0.515	23.019	0.891
CAMERINO	0.266	3.093	3.264	0.702	23.021	0.683
CASSINO	0.263	3.061	2.062	0.589	23.018	0.721
CATANIA	0.978	3.156	1.469	0.245	22.998	0.952
CHIETI – G. D'Annunzio	0.768	3.069	1.813	0.550	23.020	0.750
FERRARA	0.682	3.107	3.287	0.712	23.007	0.848
FIRENZE	0.959	3.208	2.451	0.441	23.022	0.962
FOGGIA	0.553	3.035	0.547	−0.022	23.036	0.179
GENOVA	0.576	3.179	5.100	0.651	23.032	0.902
IUAV – Venezia	0.534	3.116	2.940	0.766	23.014	0.632
L'AQUILA	0.744	3.044	2.202	0.283	23.018	0.808
LECCE	0.939	3.084	1.665	0.469	23.007	0.907
MACERATA	0.505	3.133	1.754	0.607	23.020	0.692
Mediterranea – REGGIO CALABRIA	0.632	3.067	1.861	0.333	23.017	0.813
MESSINA	0.499	3.042	4.378	0.882	23.022	0.892
MILANO	0.685	3.088	3.129	1.163	23.016	0.835
MILANO – DUE	0.599	3.043	2.512	0.657	23.013	0.797
MILANO – Politecnico	0.836	3.125	2.862	0.829	23.009	0.875
MODENA	0.537	3.162	3.341	0.924	23.004	0.825
MOLISE (CB)	0.278	3.076	1.811	0.618	23.012	0.652
NAPOLI – Federico II	0.962	3.085	1.259	0.385	23.018	0.983
NAPOLI – II Università	0.798	3.091	3.383	0.691	23.014	0.934
NAPOLI – Ist. Orientale	0.394	3.087	2.555	0.550	23.014	0.831
PADOVA	0.850	3.211	3.121	0.803	23.009	0.910
PALERMO	0.962	3.209	1.532	0.852	23.055	0.928
PARMA	0.680	3.118	2.886	0.435	23.020	0.842
PAVIA	0.541	3.150	5.118	0.930	23.005	0.819
PERUGIA	0.684	3.043	2.963	0.848	23.024	0.894
PIEMONTE ORIENTALE	0.202	3.091	2.322	0.505	23.013	0.617
PISA	0.881	3.101	2.435	1.130	23.012	0.967
ROMA – La Sapienza	0.948	3.198	2.076	0.729	23.050	0.995
ROMA – Tor Vergata	0.920	3.111	2.618	0.540	23.023	0.912
ROMA – TRE	0.756	3.067	2.010	0.447	23.020	0.884
SALERNO	0.895	3.155	1.464	0.217	23.005	0.906
SANNIO	0.033	3.087	1.970	0.542	23.010	0.585
SASSARI	0.484	3.042	2.875	0.981	23.018	0.794
SIENA	0.777	3.025	4.099	1.220	23.019	0.884
TERAMO	0.073	3.094	2.301	0.630	23.010	0.615
TORINO	0.931	3.041	3.170	1.467	23.023	0.973
TORINO – Politecnico	0.834	3.149	3.014	0.860	23.020	0.903
TRENTO	0.911	3.081	2.932	0.287	23.001	0.836
TRIESTE	0.495	3.144	4.944	0.613	22.998	0.896
TUSCIA (VT)	0.419	3.105	2.721	0.629	23.021	0.793
UDINE	0.757	3.111	2.384	0.470	23.011	0.872
VENEZIA – Cà Foscari	0.541	3.134	3.053	0.699	23.013	0.889
VERONA	0.713	3.044	2.768	0.673	23.015	0.888

Notes: Results for three very small institutions (IUSM Roma, Insubria, Catanzaro) are not reported because the model predicts negative costs. The constant (intercept) shift for the RE and RPM models is not reported as there is no variation across institutions.

Table 4. Marginal (MC) average incremental (AIC) costs

Estimates (0.000€)	Marginal costs				Average incremental costs			
% of output mean	SC	HUM	RES	PHD	SC	HUM	RES	PHD
80	4.114	2.761	0.494	31.621	3.826	3.304	0.425	15.407
100	4.368	2.703	0.460	33.773	4.008	3.382	0.374	13.505
120	4.621	2.645	0.426	35.924	4.189	3.460	0.323	11.603

Table 5. Economies of scale and scope

	Economies of scale					Economies of Scope				
% of output mean	Ray	SC	HUM	RES	PHD	Global	SC	HUM	RES	PHD
80	1.008	0.930	1.197	0.861	0.487	0.183	−0.123	−0.223	−0.063	−0.837
100	0.983	0.918	1.251	0.814	0.400	0.147	−0.110	−0.236	−0.034	−0.808
120	0.962	0.906	1.308	0.759	0.323	0.122	−0.103	−0.254	−0.012	−0.782

score can be regarded as legitimate. If, on the other hand, there is no good reason why output-specific costs are high, then the institution cannot be considered to be efficient in its production of nonscience undergraduates. What is 'good reason' is of course a value judgement typically made by policy-makers.

In Table 4, we report the average incremental costs (measured in thousands of euros) associated with each output type. We do this for a 'typical' institution with mean values of each of the outputs, and also for an institution that has 80% of these output levels and for one with 120% of the mean output levels; throughout these figures are calculated for the case of an institution that has a medical school. It is important to note that, owing to the diversity that characterizes the Italian university system, no institution actually looks like the 'typical' one described here. The figures reported in the table are therefore to be regarded as illustrative rather than definitive. We regard the estimates that arise out of the random parameter model as being more plausible than those that emerge from the random effects model; in the latter there would appear to be some upward bias to the cost estimates for doctoral study, and some corresponding downward bias in those attached to the other outputs, and so we report only the results for the former model.

As has been found in studies in other countries (for example, Johnes *et al.*, 2005), science students are more costly to teach than are nonscience students. Doctoral students are considerably more expensive to teach than are undergraduates, owing to the one-on-one supervision that they require. Our estimates suggest that science undergraduates, nonscience undergraduates and research students cost, on average, about €4000, €3000 and €14 000 per year in 2003 prices. But in interpreting these figures, the considerable measure of inter-institutional variation in output vectors noted above and in Table 1 should be borne in mind.

Table 5 reports our findings concerning economies of scale and scope, referring to the RPM model. These are startling. With the exception of nonscience undergraduates (who are already taught in very large groups, but for whom laboratory space does not impose a tight upper limit on class size) the returns to scale for all output types are diminishing. Moreover, ray returns to scale are diminishing (except in relatively small institutions); meanwhile product-specific economies of scope have been exhausted and global economies of scope are very limited. The stark lesson of these findings is that Italian universities are too big: economies could be achieved by splitting (some of) them up into smaller units.

This type of finding is unusual. In a competitive environment, a firm that is above efficient scale will typically reorganize itself so that it operates as a multiplicity of smaller units. If it were not to do so, it would risk facing damaging competition from other producers. The shielded and highly regulated environment in which Italian universities have operated has served to protect them from such competition, and has allowed (some of) them to grow to a scale that is above the optimum. This finding has very clear implications for policy.

A further issue concerns economies of scope. Product-specific economies of scope are absent, and global economies of scope are modest. Any divestment that is undertaken by institutions should bear this in mind, in that such activity should create institutions that retain the benefits of synergy.

VI. Conclusions

The use of Monte Carlo methods to provide estimates for models where the likelihood function does not yield to more conventional maximization techniques has opened up a vast array of possibilities within applied economics. In this article, we have considered the example of a random parameters stochastic frontier model, and have applied it in the context of the Italian higher education system.

Our findings suggest that there is much value in estimating models that have the flexibility to evaluate institution-specific parameters. Such models provide information about the source of cost differentials across institutions, and indicate where individual institutions need to improve their performance. In the context of Italian higher education, we have uncovered some very substantial inter-university differentials in the cost of providing education to nonscience undergraduates, and also in the costs of undertaking research. While the general picture is one of efficient provision, there are some institutions which would appear to be outliers at the bottom end. There are several examples of institutions that appear, when conducting a random effects analysis, to be fairly inefficient, but which are not so inefficient when we estimate using random parameters methods. In these cases, such as Basilicata, the costs attached to each output are higher than is typically the case, this being so for reasons other than technical inefficiency. Whether or not these unusually high costs are in some sense legitimate is, of course, a separate issue that calls for detailed and more qualitative investigation. But the method introduced here remains powerful as a means of identifying cases such as this.

Our findings on average incremental costs are reasonable and in line with studies of university costs conducted in other countries. The results on economies of scale and scope are, however, startling and have a clear policy implication. There are universities in Italy that are too big; they have exhausted scale and scope economies, and are experiencing diseconomies owing to their size.

Further work in this area should include comparative studies across countries, especially within the area covered by the Bologna agreement. As data become available for longer time frames, reworking the analysis on a longer panel would be useful. Finally, as ever in an analysis that is based on variables that summarize rather than wholly capture what is happening on the ground, our findings should be viewed alongside qualitative information about the Italian higher education system and its constituent institutions.

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