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Does econometric methodology matter to rank universities? An analysis of Italian higher education system

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A B S T R A C T

In recent years more and more numerous are the rankings published in newspapers or technical reports available, covering many aspects of higher education, but in many cases with very conflicting results between them, due to the fact that universities' performances depend on the set of variables considered and on the methods of analysis employed. This study measures the efficiency of Italian higher education using both parametric and non-parametric techniques and uses the results to provide guidance to university managers and policymakers regarding the most appropriate method for their needs. The findings reveal that, on average and among the macro-areas of the country, the level of efficiency does not change significantly among estimation approaches, which produce different rankings, instead. This may have important implications as rankings have a strong impact on academic decision-making and behaviour, on the structure of the institutions and also on students and graduates recruiters.

1. Introduction

The public budget constraints, due to recent economic crises, and the new funding mechanism of the university system (see Ref. [1] for a description of university governance in Italy), have brought back to the center of Italian academic and political debates the assessment of universities' performances. The analysis of efficiency may not be seen as the only relevant strategic issue; however, from the economic point of view it is one of the most important topics, especially in the recent period, characterized by financial constraint, growing cost pressures, and enhanced competition in the higher educational system [2].

The Italian higher education system has been reformed in last years to join the Bologna Process and universities have started being financed according to their level of virtuosity, in order to achieve higher research performances and to promote academic excellence; "formulas to allocate public funds to higher education institutions are now related to performance indicators such as graduation or completion rates" and "research funding has also increasingly been allocated to specific projects through competitive processes rather than block grants" [3]. The allocation of the resources from the government has been grounded, therefore, on a formula-based mechanism and both quantitative and qualitative indicators were developed to accurately evaluate the management of universities, their productivity in research and teaching and the overall success of their administration; as a consequence, (public) funds to higher education institutions (HEIs) are now related to performance indices according to which evaluate their management and productivity. Therefore, in recent years, measuring how well universities perform has become extremely popular and the subject of increased attention.

The statistical and econometric procedures normally used to assess the efficiency in higher education can be classified into two broad classes: parametric, such as the Stochastic Frontier Approach – hereafter SFA, and non-parametric, such as Data Development Analysis - hereafter DEA (see the seminal papers by Refs. [4] and [5]; respectively). So far, there is no general consensus about which one has to be adopted, as these two main approaches have not only

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different features, but also advantages and disadvantages [6] [1]. The former one may be useful to indicate the significant determinants of educational outcomes; the latter one, instead, can provide information on realistic targets for an inefficient university. More importantly, as Johnes [7] pointed out, "the outcomes from efficiency studies in terms of the rankings of institutions under investigation can vary according to the choice of technique (for example, parametric or non-parametric)"; Chakraborty et al. [8] also underline that before policy actions are being taken, "the stability of the technical efficiency estimates based on the parametric method should be evaluated by comparing them against those determined by the non-parametric method". Therefore, from a political and a managerial standpoint, these diverging results could lead to potentially ineffective decisions. To the best of our knowledge, only few studies have compared DEA to stochastic frontier efficiencies in the higher education context [9,10] even though such comparison has already been applied in the context of school districts [8], local education authorities [11], electricity distribution utilities [12], port industry [13], institutions providing training [14] and using simulations [15,16]. See Johnes [7] for a review and a comparison of the techniques for measuring efficiency. The evidence suggests that the choice of the techniques could affect efficiency scores which wouldn't be an issue in case both methods provide the same ranking but would be, instead, more problematic from a managerial perspective in case no consensus emerge on the group of high and low performing institutions classified. This is not a secondary issue in terms of policy implications as university managers as well as policy makers might choose the estimation approach which is more convenient for them and that best reflects their own preferences (see Ref. [17] on this point).

The first objective of the paper is studying the efficiency of Italian HEIs using data over the four-years from 2008 to 2011, exploiting both parametric and non-parametric methods.

In the non-parametric approach, in order to obtain unbiased coefficients, technical efficiency estimates have been firstly obtained by applying a DEA two-stage with a bootstrap procedure introduced by Simar and Wilson [18]; through which DEA efficiency scores are obtained in the first step and then regressed, in the second step, on potential covariates with the use of a bootstrapped truncated regression. Alternatively, we also apply a so-called double-bootstrap method in which DEA scores are bootstrapped in the first stage to obtain bias corrected efficiency scores, and then a second stage is performed on the basis of the bootstrapped-truncated regression. For an application of such methods in higher education, see Wolszczak-Derlacz and Parteka [19] and Curi et al. [20]. See also Cotte [21] for an application of a two-stage procedure where DEA is performed in the first the stage and a Maximum likelihood estimation is applied in the second step.

Considering the parametric approach, the most recent literature [22,23] emphasized the importance of separating inefficiency and fixed individual effects. Indeed, the efficiency scores may suffer from the presence of incidental parameters (number of fixed-effect parameters) or time-invariant effects, often unobservable, that may distort the estimates. Wang and Ho [23]; in order to incorporate heterogeneity in panel data in the stochastic frontier model, show that first-difference and within transformation can be analytically performed to remove the fixed individual effects, and thus the estimator is immune to the incidental parameters problem (the latter being somehow affecting the methods proposed by Ref. [22]). Moreover, the presence of a multidimensional nature of the production (i.e. multiple outputs) may represent a problem when estimating a stochastic production models. To solve this issue, a distance function approach could been considered [24,25]. This technique is particularly useful when no price information, regarding inputs and outputs, is available [26,27] and [10]. Therefore, we employ a Stochastic Frontier Analysis, modelling the production set through an output distance function, using a within transformation to data as developed by Wang and Ho [23].

The second contribution of this study, beyond the analyses on HEIs' performances already performed in the literature, is bringing new evidence on the importance of using the efficiency estimates derived from various estimation methods (i.e. both parametric and non-parametric techniques) to rank universities. Indeed, in recent years, more and more numerous are the rankings published in the newspapers or technical reports available, covering several aspects of higher education, but in many cases with very conflicting results between them (see Ref. [28] for a detailed discussion). This exercise provide guidance to university managers and policymakers, warning them that the estimates of the level of efficiency could vary by estimation techniques and, more importantly, that the ranking of universities may change; this is particularly relevant considering that rankings have a strong impact on academic decision-making and behaviour, and on the structure of the institutions [29], that HEIs are focusing on the criteria with the highest impact on the ranking [30], and that also students and graduates recruiters follow the hierarchy of institutions (see Refs. [31–33]). In other words, as both human and financial resources might depend on how the university is positioned in such classifications, it is useful providing further light on the delicate processes of evaluating the efficiency of HEIs.

Finally, the third goal of the paper is to analyse exogenous factors which potentially affect university (in)efficiency such as some institutional details and characteristics of the market place and of the regions where the universities are located.

The rest of the paper is organized as follows. In Section 2, we present the methodological approaches; Section 3 illustrates the data, production set and model specification for the empirical analysis; Section 4 contains the main results. Finally, Section 5 discusses the managerial and policy implications of the main findings with concluding remarks.

2. Empirical methodology

2.1. Double-bootstrap Data Envelopment Analysis

Until a few years ago, in the DEA standard technique, Tobit-estimator was used to compute the inefficiency analysis in the second step. However, Simar and Wilson [18] have emphasized two possible problems stemming from applying Tobit in this context. First, the results may be biased in the presence of serial correlation between variables at the two stages. Second, the efficiency scores may be biased in finite samples. To obtain unbiased beta coefficients with valid confidence intervals, we follow the double-bootstrap procedure suggested by Simar and Wilson [18]; where DEA scores are bootstrapped in the first stage to achieve bias corrected inefficiency scores and explained in a bootstrapped truncated regression with discretionary explanatory variables. Therefore, in this paper we firstly analyse the technical efficiency using a double-bootstrap DEA method [18]. In particular, we focus on an output-oriented model, following Agasisti and Dal Bianco [34]; who claimed that "as Italian universities are increasingly concerned with reducing the length of studies, and improving the number of graduates, in order to compete for public resources, the output-oriented model appears the most suitable to analyse higher education teaching efficiency". Moreover, output oriented models seem to be particularly appropriate in the context of tertiary

[1] See Johnes [10] for a description of the parametric and non-parametric approaches' properties.

education according to the fact that the resources used can be considered fixed and that universities cannot influence, at least in the short run, the human, financial and physical capital available [35]. Therefore, we present an output-oriented model. Suppose that a Decision Making Unit (DMU) — in our case the university - can be characterized by a technological set Ψ defined as:

$$\Psi = \left\{ (x, y) \in \Re^N \times \Re^M \middle| \, x \; can \; produce \; y \right\} \tag{1}$$

where x represents a vector of N inputs and y the vector of M outputs.

Specifically, we use a Farrell/Debreu output-oriented technical efficiency measure such as:

$$\delta_j(x, \; y) = \max\{\theta : (x, \theta y) \in \Psi\} \tag{2}$$

where θ measures the maximum possible increase in output y, given that inputs x remain constant.

We assume variable return to scale (VRS); the DEA-VRS is probably the most reliable in our case as suggested by Agasisti [36]; who argued that the assumption of constant return to scale is restrictive because it is reasonable "that the dimension (number of students, amount of resources, etc.) plays a major role in affecting the efficiency" especially if we consider, as we do, the DMUs trying to achieve pre-determinate outputs, given certain inputs.

Thus, at the first stage, we estimate equation (1) through the following linear programming:

$$\widehat{\delta}_i = \max_{\gamma} \left\{ (x, y) \in \Re^N \times \Re^M : \sum_{i=1}^{n} \gamma_i y_i \geq y; \sum_{i=1}^{n} \gamma_i y_i \leq x \right\} such \; that \; \gamma_i \geq 0, \; i = 1, \ldots, n \tag{3}$$

where y is a $I \times 1$ vector of constants.

In the second stage, we use the DEA efficiency scores (calculated in the first step) as dependent variable ($\widehat{\delta}_i$) regressing them on potential exogenous environmental variables (z_i):

$$\widehat{\delta}_i = z_j \beta + \varepsilon_j \qquad j = 1, \ldots, n \tag{4}$$

where ε_j is a statistical noise.

A problem may arise due to the fact that true DEA scores, obtained in the first step, are unobserved and replaced by previously estimates $\widehat{\delta}_i$, which, in turn, are serially correlated in an unknown way; moreover, the disturbance error ε_j is correlated with z_i as a consequence of the fact that inputs and outputs can be correlated with the environmental variables. To solve these issues, we use a consistent bootstrap approximation of the efficiency distribution, in which DEA scores are bootstrapped in the first stage, to obtain bias corrected efficiency scores; then, in the second stage, in order to analyse the dependency of the efficiency on a set of potential covariates, we apply a consistent bootstrap-truncated regression to consistently estimate the parameters by using maximum likelihood and for inference. We also use a two-stage DEA analysis where the efficiency scores are obtained in the first step and then they are regressed, in the second stage, on potential covariates, using again a bootstrap-truncated regression.

All variables are measures in log-level in order to interpret the estimated coefficients as elasticities. To obtain the DEA efficiency scores, we utilize Wilson's FEAR 1.15 software [37] which is freely available online, and the truncated regression models were then performed in STATA 14 software.

2.2. A stochastic education distance frontier

The analysis explores also the Stochastic Frontier Analysis, because it offers useful information on the underlying education production process, as well as information on the extent of inefficiency. Nowadays, the most widely applied SFA technique is the model proposed by Battese and Coelli [38]; to measure technical efficiency across production units. Intuitively, technical efficiency is a measure of the extent to which an institution efficiently allocates the physical inputs at its disposal for a given level of output. The presence of a multidimensional nature of the production (i.e. multiple outputs) may represent a problem when estimating a stochastic production models. To solve this issue a distance function approach has been considered [24,25]. Moreover, this technique is particularly useful when no price information regarding inputs and outputs is available [27]. In line with Abbott and Doucouliagos [39] and Johnes [10]; we choose to model the production set through an output distance function in a panel context. Moreover, on a methodological ground, the most recent literature, which deals with panel data, emphasized the importance of separating inefficiency and fixed individual effects. Indeed, the efficiency scores may suffer from the presence of incidental parameters (number of fixed-effect parameters) or time-invariant effects, often unobservable, that may distort the estimates [22,23]. For instance, students' or researchers' (average) innate abilities may be an important determinant of their individual academic achievements and thus account for a share of the heterogeneity in data when evaluating the efficiency of the institution in which they are studying or working.[2] As Wang and Ho [23] have underlined: "(…) stochastic frontier models do not distinguish between unobserved individual heterogeneity and inefficiency", forcing "all time-invariant individual heterogeneity into the estimated inefficiency". In order to deal with this problem and to estimate the technical efficiency, we apply a procedure developed by Wang and Ho [23]; according to whom after transforming the model by either first-difference or within-transformation, the fixed effects are removed before estimation. More specifically, we impose on the data a within transformation; as Wang and Ho [23] specified, "by within-transformation, the sample mean of each panel is subtracted from every observation in the panel. The transformation thus removes the time-invariant individual effect from the model". Following the notation in Wang and Ho [23]; the transformation employed in our model is (being w, for instance, any input or output to be transformed):

$$w_{i.} = (1/T) \sum_{t=1}^{T} w_{it}, \; w_{it.} = w_{it} - w_{i.} \tag{5}$$

The stacked vector of $w_{it.}$ for a given i is:

$$\tilde{w}_{i.} = (w_{i1.}, w_{i2.}, \ldots, w_{iT.})' \tag{6}$$

For simplicity, hereafter in our formulation does not include a subscript t[3]. The baseline model associated to distance function after the transformation can be written as:

[2] In the context of the use of efficiency models for policy-making, or managerial considerations, the problem of separating the three elements: (i) unobserved structural differences in underlying inputs, (ii) inefficiency and (iii) production process is of crucial importance. Indeed, the lack of judgment about the various parts would lead to a misleading evaluation of estimated inefficiency.

[3] Even though the formulation does not include a subscript t, the inefficiency component is time varying in order to examine how the (in)efficiency changes over time.

$$f(\tilde{y}_{i.}) = f(\tilde{x}_{1.}, \ldots \tilde{x}_{n.}) + \tilde{\varepsilon}_{i.} \quad (7)$$

where $\tilde{y}$ represent the conventional outputs, $\tilde{x}$ denote the conventional inputs and $\tilde{\varepsilon}$ denotes the disturbance term. Following a common practice, we now assume a functional form a' la Cobb-Douglas for the output distance function:

$$ln\tilde{D}^{o}_{i.} = \sum_{m=1}^{M} \tilde{\alpha}_m ln\tilde{y}_{mi.} + \sum_{k=1}^{K} \tilde{\beta}_k ln\tilde{x}_{ki.} + \tilde{v}_i \quad (8)$$

By a within transformation, α_i (intercept that changes over time according to a linear trend with unit-specific time-variation coefficients and that represents time-invariant effects) disappears from our specification. Normalizing by $\tilde{y}_i$[4], that guarantees the linear homogeneity of degree 1 in outputs ($\sum_{m=1}^{M}\tilde{\alpha}_m = 1$) as suggested by Lovell et al. [25]; the output oriented distance function becomes:

$$ln\left(\frac{\tilde{D}^{o}_{i.}}{\tilde{y}_{i.}}\right) = \sum_{m=1}^{M} \tilde{\alpha}_m ln\tilde{y}^{*}_{mi.} + \sum_{k=1}^{K} \tilde{\beta}_k ln\tilde{x}_{ki.} + \tilde{v}_i \quad (9)$$

where $\tilde{y}^{*}_{mi.} = \tilde{y}_{mi.}/\tilde{y}_{i.}, \tilde{y}^{*}_{ni.} = \tilde{y}_{ni.}/\tilde{y}_{i.}$ and thus $\tilde{y}_{i.} = 1$. In addition, the time dummies are also taken into account in order to capture exogenous or business cycle effects that can influence the production process of the decision-making units (i.e. universities). It's obvious that $ln(\tilde{D}^{o}_{i.})$ is not observable. Then, in order to solve this problem, we can re-written $ln(\tilde{D}^{o}_{i.}/\tilde{y}_{i.}) = ln(\tilde{D}^{o}_{i.}) - ln(\tilde{y}_{i}.)$. Thus, we transfer $ln(\tilde{D}^{o}_{i.})$ to the residuals, i.e. on the right and side of equation (9), and using $-ln(\tilde{y}_{i.})$ as dependent variable [24]. In our case, we follow Paul et al. [40]; i.e. imposing $ln(\tilde{y}_i)$. equation (9) thus becomes:

$$ln(\tilde{y}_{i.}) = \sum_{m=1}^{M} \tilde{\alpha}_m \ln\left(\tilde{y}^{*}_{mi.}\right) + \sum_{k=1}^{K} \tilde{\beta}_k ln\tilde{x}_{ki.} + \tilde{v}_i - \tilde{u}_i \quad (10)$$

where $\tilde{u}$ terms stands for inefficiency component, obtained from the truncation to zero of the distribution $N(\tilde{m}_i, \tilde{\sigma}^2_u)$, where $\tilde{m}_i = \tilde{\mu} + \tilde{z}_i\tilde{\delta}$, $\tilde{\mu}$ denoting the location parameter, $\tilde{z}_i$ a vector of determinants of (technical) efficiency and $\tilde{\delta}$ is a vector of unknown coefficients; indeed $\tilde{v}$ denotes the vector of random variables assumed to be i.i.d. $N(0, \tilde{\sigma}^2_v)$ and independent of the $\tilde{u}$. In other words, the inefficiency of university i is assumed to systematically vary with respect to some determinants (see Section 3 below for more detail on production set). Time dummies are also included in order to capture the influence of exogenous factors. In this analysis, we do not impose the "scaling property" (for more details see Wang and Schmidt [41] and Alvarez et al. [42] because produces estimation problems in our model. In fact, as suggested in literature (see for instance [23]), whether the scaling property holds in the data is ultimately an empirical question. In other words, we assume changes not only in scale but also in the shape of the inefficiency distribution.

With stochastic frontier analysis, a frontier is estimated on the relation between inputs and outputs. This can, for example, be a linear function, a quadratic function or a translog function. However, there is no general consensus about which one has to be adopted in the higher education environment (for a discussion on the different function forms, see Refs. [43] and [44]; see also [45]; where the authors consider both a Translog and a Cobb-Douglas finding that the functional form chosen seems to have a minor impact on main estimates). More specifically, the assumptions behind the use of Cobb–Douglas production functions are plausible in view of the theoretical model which describes the human capital formation in the university system. It allows overcoming the multicollinearity problem associated to estimate a few number of parameters with respect to the Translog function; therefore it is less susceptible to multicollinearity and degrees of freedom problems than the Translog (see Ref. [46]; who uses a Cobb-Douglas function in order to model exogenous variables in human capital formation).[5] On the other hand, instead, concerning the structure of production possibilities, a more general functional form, that is, the transcendental logarithmic, or "Translog", could be considered for the frontier production function. The Translog functional form may be preferred to the Cobb–Douglas form because of the latter's restrictive elasticity of substitution and scale properties, it allows for non-linear causalities, compared with the more simple Cobb-Douglas function (see Ref. [47]; who use a Translog function in order to compare the efficiency of public universities among European countries). While the theoretical problem of identifying the correct functional form of HEIs' production processes is discussed in the literature, empirical tests about how different forms affect estimations are quite sparse. The topic itself is important in a managerial perspective; indeed, it is relevant to check whether the judgment about efficiency is affected by the assumptions behind the production process or not. Therefore, this paper uses both a Translog and a Cobb-Douglas production function.

The validity of the heteroschedastic assumption is tested using a Likelihood Ratio (LR) test which allows us to identify the fit of the model and to confirm the imposition of some determinants in the inefficiency term. All coefficients of the output distance function, estimated through a maximum likelihood estimator (MLE), and technical efficiency are obtained using the STATA 12 software.

3. Data, the production set and model specification

3.1. Selected inputs and outputs

The dataset refers to Italian public universities over the four years period 2008–2011 and it has been constructed using data which are publicly available on the Italian Ministry of Education, Universities and Research (MIUR) Statistical Office website. We exclude all private sector universities, due to the absence of comparable data on academic research; this leaves us with a sample of 53 universities, each of which yields data over the four-year period, so we have a total of 212 observations. The sample is very representative of the higher education system in Italy, corresponding to almost 90% of the total number of public universities in the country

[4] Since they are mathematically equivalent, the choice of the normalizing variable is innocuous when using stochastic frontier models (see Ref. [93]). More importantly, using a similar empirical method to the one we have used in the paper, such as a stochastic output distance frontier, Abbott and Doucouliagos [26] outlined that "It is necessary to impose a number of constraints on the output distance function in order to ensure homogeneity of degree one in outputs, as well as symmetry (see Ref. [92]). This can be achieved by choosing arbitrarily one of the outputs as the normalizing variable; in this paper, research performance is used to serve this role". Therefore, following Abbott and Doucouliagos [26], we decide to normalize by research grants. However, for robustness, we also conduct a sensitivity analysis normalizing by the number of graduates weighted by their degree classification. Results (available on request) are similar.

[5] Moreover, in our case the presence of zero values for any inputs or outputs related to the choice of the functional forms does not represent a problem as we do not have any zero values for inputs and outputs; therefore, when we take the log values of both inputs and outputs, there was no need to omit universities with any zero values, thus without implications for the representativeness of the resulting sample.

(we are not able to cover the complete population of universities due to missing information on some of the variables used in the analysis); moreover, the 53 universities included in the empirical analysis cover the 88% of the students enrolled in the entire higher public education system in Italy.

Referring to the literature on this subject, the production technology is specified, with four inputs: 1 – number of academic staff; 2 - percentage of enrolments with a score higher the 9/10 in secondary school; 3 – the percentage of enrolments who attended a lyceum; 4 - total number of students.[6] More specifically, the first input is the number of academic staff ($ACAD_{STAFF}$).[7] It is a measure of a human capital input and it aims to capture the human resources used by the universities for teaching activities (see Refs. [10,34]) such as the total academic staff adjusted for the respective academic position (i.e. professors, associate professors, assistant professors and lectures).[8] The second and third inputs are the percentage of enrolments with a score higher the 9/10 in secondary school (ENR_{HSG}) and the percentage of enrolments who attended a lyceum[9] (ENR_{LYC}), with respect to the total number of students enrolled. Indeed, among the inputs that are commonly known to have effects on students' performances there is the quality of the students on arrival at university. There is strong evidence that the type of secondary high school and pre-university academic achievement are important determinants of the students' performances [48–51]. The underlying theory is that the ability of students lowers their educational costs and increases their motivation [52]. Thus these two inputs aim to capture the quality of students on arrival at university (i.e. proxies of the knowledge and skills of students when entering tertiary education).[10] The fourth and last input is the total number of students (STUD) in order to measure the quantity of undergraduates in each university [34].

Moving to the output side, two measures are included in the model reflecting the teaching and research functions of HEIs[11]: 1 – number of graduates weighted by their degree classification; 2 – research grants. According to Catalano et al. [53] "the task assigned to universities is to produce graduates with the utilization and the combination of different resources" and Madden et al. [54] used the number of graduates under the hypothesis that the higher is the number of graduates the higher is the quality of teaching. Also Worthington and Lee [55] considered the number of undergraduate degrees awarded an obvious measure of output for any university; similarly, Eckles [56] used the graduation rate. Thus, the first output included in the analysis is the number of graduates weighted by their degree classification[12] ($GRAD_{MARKS}$), in order to capture both the quantity and the quality of teaching (see also [54,57,58]. As the focus of the paper is on both teaching and research, we include as an output also a measure of research performances of the universities. Academic research is the most controversial output and different proxies have been used in the literature such as bibliometric indicators and peer review [59], weighted indexes of publications and number of research articles [60–65]. Information on the number of publications is not available to us, thus we use research grants (RES) as a second output and as a proxy of research outputs (see Refs. [39,55,66–69]). We follow Agasisti and Johnes [67]; who underlined that "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". Research grants reflect the market value of the research conducted and can, therefore, be considered as a proxy for output [70,71]. Specifically, in our case, it represents the sum of research grants provided by the Italian Ministry of Education (MIUR) for basic research (the so called PRIN projects) and the other amounts provided by MIUR and other Ministries for basic and applied research. The criteria for allocating the grants is based on the quality of research proposals, and to the track record of past results obtained by research groups' proponents. Also, the distribution of research funds obtained in the different years allows considering the multi-year nature of research activities at institution level, in which different research groups obtain grants in different years. It is important to recall that our measure does not represent the final research's final output anyway, as it would be better represented by the final step of activities conducted, such as the academic publications, reports, patents, etc. – in this perspective, grants are much more surely an output, but an intermediate one. We are aware that the use of grant income might raise some problems related to the presence of a lag between the publication of research output and the generation of that research; however, according to Hashimoto and Haneda [72] this is more important when using citation counts or number of patents than research income measure. Moreover, according to Johnes [10]; the use of research grants as an output "is also an attractive measure of research in that it provides an up-to-date picture of research activity and output in the current academic year".[13] Thus, also considering that there are no clear criteria for deciding on the appropriate length of lag [73] and following Johnes [10]; we use a static model in our analysis.

[6] There are no measures of capital inputs (such as library, computing, buildings) which might have a role in determining university outputs; unfortunately such data are very difficult to obtain for Italy. This is confirmed by a recently published paper by De Witte and López-Torres [89] in which they reviewed the literature regarding the efficiency in education. In describing the inputs in the education production function, only a very small amount of paper included those inputs in the analysis in higher education.

[7] We have also considered non-academic staff in order to take into account the administrative staff who support the academic staff and the students. As the results (available on request) are similar, we decide to use only the academic staff.

[8] We assign weights to each category according to their salary and to the amount of institutional, educational and research duties the academic staff has to deal with (see Refs. [54,61,90]) as follows: Academic Staff ($ACAD_{STAFF}$) = 1*professors+0.75*associate professors+0.50*assistant professors +0.25*lectures. A potential limitation of this choice is represented by the decision to assign different weights. Therefore, for robustness, we also further test how alternative weights given to this variable would change the results, to avoid a sever discounting of assistant professors and lectures. In all cases results (available on request) are similar.

[9] For the readers who are not familiar with the characteristics of the Italian secondary school system, in Italy, students before entering at University attend five years of high school. Lyceum is a non-vocational secondary school being more academic oriented and specialized in providing students the skills needed in order to enroll in the university.

[10] We look at the correlation between ENR_{HSG} and ENR_{LYC}. Both Pearson and Spearman correlation coefficients are positive and statistically significant, but their magnitude does not suggest to have concerns regarding multicollinearity problems. In other words, we believe these variables control for two different aspects of pre-enrollment characteristics such as the quality of the secondary school attended (secondary school track chosen) and the secondary high school grade (a measure of academic preparedness). Correlation coefficients are not presented in the paper due to space constraints and available on request.

[11] Unfortunately, due to the unavailability of data, we are not able to consider what is known to be the third function of the universities such as knowledge transfer to industry and links of HEIs with industrial and business surroundings.

[12] In Italy students can graduate obtaining marks from 66 to 110 with distinction. In order to weight the graduates according to their degree marks, we apply the following procedure: $GRAD_{MARKS}$ = 1* graduates with marks between 106 and 110 with distinction +0.75*graduates with marks between 101 and 105 + 0.5*graduates with marks between 91 and 100 + 0.25*graduates with marks between 66 and 90. The weights have been chosen so that the distance between two ranks is $1/4 = 0.25$. For robustness, we also further test how alternative weights given to the $GRAD_{MARKS}$ variable, to avoid a severe discounting of the students earning less than top marks, would change the results; we've also used just the number of graduates without weighting by their degree classification. In all cases results (available on request) are similar.

[13] See also Frey and Rost [91] for a discussion on the appropriate measures of research quality and quantity.

Table 1
Definition of the variables and descriptive statistics – Mean values by geographical areas.

		Mean values			
		North-Western	North-Eastern	Central	Southern
Inputs					
$ACAD_{STAFF}$ [a]	# of academic staff (university level)	1043.56 (648.21)	1061.50 (832.26)	1221.82 (893.12)	797.75 (641.73)
ENR_{HSG} [b]	% of enrolments with a score higher than 9/10 in secondary school (university level)	3.29 (0.96)	3.41 (0.70)	3.54 (1.05)	3.48 (1.05)
ENR_{LYC} [b]	% of enrolments who attended a lyceum	8.68 (1.68)	7.92 (206)	8.37 (2.15)	7.78 (1.41)
STUD	Total number of students (university level)	29147.55 (18022.32)	28583.58 (22975.21)	37425.35 (32750.00)	26882.18 (20765.05)
Output					
$GRAD_{MARKS}$	# of graduates weighted by their degree classification (university level)	3082.15 (1951.83)	3241.96 (2649.28)	4225.42 (3634.122)	2435.71 (1962.20)
RES	Research grants (university level)	1.17e+07 (7729784)	1.09e+07 (9783430)	1.25e+07 (9960390)	5808383 (5449196)
Explaining the inefficiency					
MED	Medical School	0.727 (0.450)	0.800 (0.405)	0.675 (0.474)	0.590 (0.494)
FPS	Fees per student (regional level)	1157.13 (248.55)	1202.83 (224.98)	843.95 (205.94)	588.47 (130.36)
MK	Market share (university level)	0.272 (0.297)	0.300 (0.200)	0.400 (0.343)	0.363 (0.290)
YEAR_FOND	Year of foundation	1803.18 (246.41)	1602.30 (1657.02)	1657.02 (342.32)	1845 (215.90)
WOMEN	# of females among students	15655.66 (11505.99)	16317.90 (12888.19)	21310.80 (19645.51)	16078.85 (12623.57)
GDP	Gross domestic product (regional level)	28.62 (2.43)	27.30 (1.04)	25.40 (1.76)	15.83 (1.57)
FD_1	Financial Development (1)	165.86 (58.24)	99.87 (9.43)	114.48 (12.81)	24.04 (10.54)
FD_2	Financial Development (2)	71.00 (12.29)	54.83 (5.10)	65.54 (18.42)	19.20 (8.64)

Note: Authors calculation on data collected by the Italian Ministry of Education, Universities and Research Statistical Office.
[a] In order to get an easy and comprehensible measure, the total number of academic staff is reported in the descriptive statistics. In the analysis, the total number of academic staff has been, instead, adjusted for their respective academic position (i.e. professors, associate professors, assistant professors and lectures).
[b] Both ENR_{HSG} and ENR_{LYC} are percentages of the total number of students enrolled.

When looking at the descriptive statistics (Table 1 below), it is interesting to notice that, considering the four geographical areas in which we have aggregated the universities and taking into account the inputs, the Southern area shows the lowest number of academic staff and, interestingly, the highest percentage of enrollments with a score higher than 9/10 in secondary school. The number of students is, instead, more stable across the areas. Considering the performances (output side) by geographical areas, the North-Central areas outperform the Southern area both considering the number of graduates weighted by their degree marks and the grants received for the research activities.

3.2. Factors affecting university (in)efficiency

At this stage, DEA and SFA scores are linked with several factors, related to the institutional details and some characteristics of the marketplace and the environment where the institutions are located, that may influence universities' performances. These factors are modelled as variables, which directly influence the variability of the inefficiency term. In other words, they affect the efficiency with which inputs are converted into outputs. The model to be estimated takes on the following form:

$$\delta_{i,j,t} = \alpha + \beta_1 MED_{i,j,t} + \beta_2 FPS_{i,j,t} + \beta_3 MK_{i,j,t} + \beta_4 MK^2_{i,t} + \beta_5 YEAR\_FOND_{i,j,t} + \beta_6 WOMEN_{i,j,t} + \beta_7 GDP_{j,t} + \beta_8 FD_{j,t} + u_{i,j,t} \tag{11}$$

where i refers to single university, j the region where it is located and t denotes time period; *MED* is a dummy variable equalling 1 if the university has a Medical Faculty and 0 otherwise; it has been included in order to take into account the specificity of faculty composition (see Ref. [74]); for a similar approach); *FPS* represents the fees per student calculated as the ratio of the amount of income received by the university from the fees paid by the students over the total number of students, in order to take into account the services offered by the institution (the association between efficiency and fees of Italian universities has already taken into account by Refs. [75] and [45] as well as the relationship between fees and level of enrolment by Ref. [76]; *MK* is the market share measured as the ratio between the number of enrolments at university i and the total number of enrolments in the universities located in the same region, included for capturing the potential effects due to the presence of more concentration or competition between universities; indeed, the market structure of the HEIs could play an important role in calculating the efficiency, as an increase in competition in the higher education sector could lead to greater efficiency (see Refs. [45,77,78] for a discussion); *YEAR_FOND* is the year of foundation of the university as a proxy for the level of tradition of a given HEIs as, according to [19]; it is often perceived that HEIs with a longer tradition have a better reputation, but it could also be the case that younger HEIs have more flexible and modern structures, assuring a more efficient performance; *WOMEN* is the number of females among students in order to test the relation between the gender composition of the students and universities' efficiency scores; *GDP* is the gross domestic product corresponding to the total production of economic goods and services, with the aim of controlling for the growth of the economic system, as the university location can be an important determinant of its performance (the idea that rich and poor areas offer different surroundings has been already explored, with alternate results, by Ref. [79] for secondary schools and [74,80]; and [19]; for higher education); *FD* represents the financial development measured as aggregate private credits relative to GDP (as robustness we also use aggregate private deposits relative to GDP); finally, u is the vector of error terms. We measure *MED*, *FPS*, *MK*, *YEAR_FOND* and *WOMEN* at university level, while *GDP* and *FD* are instead measured at regional level. Time dummies have been included with the aim of capturing the inefficiency changes over time. See Table 2 below, for more details on the specification of inputs, outputs and exogenous factors.

4. Results

4.1. Efficiency scores

Table 3, below, presents the estimated parameters from the DEA

Table 2
Specification of inputs, outputs and exogenous factors.

Inputs	$ACAD_{STAFF}$; ENR_{HSG}; ENR_{LYC};STU
Outputs	$GRAD_{MARKS}$; RES
Explaining the inefficiency	MED; FPS; MK; YEAR_FOUND; WOMEN; GDP; FD_1; FD_2

$ACAD_{STAFF}$: # of academic staff.
ENR_{HSG}: % of enrolments with a score higher than 9/10 in secondary school.
ENR_{LYC}: % of enrolments who attended a lyceum.
STU: Total number of students.
$GRAD_{MARKS}$: # of graduates weighted by their degree classification.
RES: Research grants.
MED: Medical School.
FPS: Fees per student.
MK: Market share.
YEAR_FOND: Year of foundation.
WOMEN:# of females among students.
GDP: Gross domestic product.
FD_1: Financial Development (aggregate private credits/GDP).
FD_2: Financial Development (aggregate private deposits/GDP).

Table 3
Two-stage bootstrap DEA technical efficiency over the period 2008–2011 by geographical areas.

	2008			2009			2010			2011			Tot		
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(l)	(m)	(n)	(o)	(p)	(q)
	No boot	Boot	Bias	No boot	Boot	Bias	No boot	Boot	Bias	No boot	Boot	Bias	No boot	Boot	Bias
Geographical areas															
North-Western	0.7575	0.6313	0.1262	0.8026	0.6735	0.1291	0.8547	0.7629	0.0918	0.8732	0.7943	0.0789	0.8220	0.7155	0.1065
North-Eastern	0.7221	0.5932	0.1289	0.7936	0.6713	0.1223	0.8777	0.7843	0.0934	0.8906	0.8123	0.0783	0.8210	0.7153	0.1057
Central	0.8990	0.6713	0.2277	0.8453	0.6733	0.1720	0.8909	0.7728	0.1181	0.9158	0.8112	0.1046	0.8877	0.7322	0.1555
Southern	0.7441	0.5958	0.1483	0.7215	0.5987	0.1228	0.7463	0.6571	0.0892	0.8008	0.7178	0.0830	0.7532	0.6423	0.1109

Notes:
(a)-(d)-(g)-(l)-(o): Report estimates of DEA efficiency scores not-bootstrapped in the first stage; (b)-(e)-(h)-(m)-(p): Report estimates of DEA efficiency scores bootstrapped in the first stage; (c)-(f)-(i)-(n)-(g): Report Bias refers to the bias found in the estimation.

analysis as described in Section 2.1. The dependent variable is Farrell's bias corrected efficiency score of the i-th university derived from DEA estimates. Table 3 reports both standard efficiencies (No boot – i.e. DEA scores are not bootstrapped) and bias corrected efficiencies (Boot – i.e. DEA scores are bootstrapped) as well as the bias found in our estimation (Bias).

First of all, our evidence suggests the importance of using a double-bootstrapped DEA approach; indeed, the main results are confirmed but a strong bias is found in our estimation, meaning that the efficiency scores calculated without bootstrap might be over-estimated. Examination of Table 3, shows the presence of some geographical effects (by macro-areas) with institutions in the Central-North area (North-Western, North-Eastern and Central) outperforming those in the Southern area; this is customary for the literature on Italian universities (see, e.g., [34]). Taking the average across years into consideration (last three columns of Table 3), the estimated gap of efficiency scores is in the order of slightly less than 10% between the Central-North regions of the country and the Southern one; for instance the average efficiency of the North-Eastern area is estimated around 72% - in other words, the output expected can be expanded by around 28% using the same amount of inputs. Instead, the Southern area is around 64%, thus their inputs can be used more efficiently for producing around three/fourth more outputs. Tables 4 and 5 below, instead, present the estimated parameters of the stochastic education distance frontier presented in Section 2.2. (both for the Cobb-Douglas and Translog production function); from a methodological perspective, the null hypothesis that there is no heteroscedasticity in the error term has been tested and rejected, at 1% significance level, using a Likelihood Ratio Test (LR), giving credit to the use of some exogenous variables, according to which the inefficiency term is allowed to change. In other words, the validity of heteroscedastic assumption has been confirmed, leading to the significance of the inefficiency term. The coefficients show that all the inputs variables have a positive and statistically significant effects on the various outcomes of the universities.[14] The geographical effects (by macro-areas) already found are confirmed with regions in the Central-North area still outperforming those in the Southern area.

Table 6, below, summarizes the efficiency estimates for each university in the sample. When looking at the non-parametric estimates (DEA efficiency scores), the mean efficiency of all universities is 0.6882 (to confirm the importance of obtaining the bootstrapped efficiency scores, the mean efficiency of all universities is 0.8056 without the bootstrapping procedure), with slightly more than 50% of the universities having a level of efficiency over the sample mean. Again, it is clear than the universities located in the Central-North area perform better than those in the Southern area (75% of the universities with a level of efficiency over the sample mean are located in the Central-North area). Still taking into account the geographical effects, some information could be gained also when we consider the big city areas where many universities are located. For instance, the Rome area (where Roma La Sapienza, Roma Tor Vergata and Roma Tre are located), is particularly efficient with an average efficiency of 0.7437 among all the years. The Milan area (where Milano University, Milano Bicocca and Milano Politecnico are located) also shows good performances with an average of 0.8090 among all the years. Finally the Naples area (where Napoli Federico II, Napoli II, Napoli L'Orientale and Napoli Parthenope are located), shows lower performances with an average of 0.6465

[14] LR test coefficients as well as coefficients of inputs and outputs are not showed in the paper due to space constraints, but they are available on request.

Table 4
SFA directional output distance efficiency scores over the period 2008–2011 by geographical areas – Cobb-Douglas production function.

	Model A					Model B					Model C				
	2008	2009	2010	2011	Tot	2008	2009	2010	2011	Tot	2008	2009	2010	2011	Tot
Geographical areas															
North-Western	0.7266	0.7102	0.7696	0.7978	0.7511	0.8254	0.8316	0.8666	0.8732	0.8492	0.7201	0.7035	0.7631	0.7923	0.7447
North-Eastern	0.7596	0.7384	0.8206	0.8499	0.7906	0.8400	0.8516	0.9050	0.9144	0.8768	0.7514	0.7293	0.8121	0.8419	0.7822
Central	0.8091	0.7790	0.8303	0.8389	0.8143	0.9060	0.9005	0.9157	0.9158	0.9095	0.8016	0.7705	0.8218	0.8309	0.8062
Southern	0.5661	0.5370	0.6054	0.6436	0.5880	0.6472	0.6411	0.6891	0.7095	0.6717	0.5578	0.5287	0.5963	0.6353	0.5795

Notes:
In model A, ME, FPS, MK, YEAR_FOUND, WOMEN and GDP have been used as determinants of inefficiency; In model B, ME, FPS, MK, YEAR_FOUND, WOMEN and FD_1 have been used as determinants of inefficiency; In model C, ME, FPS, MK, YEAR_FOUND, WOMEN and FD_2 have been used as determinants of inefficiency.

Table 5
SFA directional output distance efficiency scores over the period 2008–2011 by geographical areas – Translog production function.

	Model A					Model B					Model C				
	2008	2009	2010	2011	Tot	2008	2009	2010	2011	Tot	2008	2009	2010	2011	Tot
Geographical areas															
North-Western	0.7824	0.8318	0.8852	0.8876	0.8468	0.7803	0.8303	0.8844	0.8865	0.8454	0.7795	0.8298	0.8855	0.8876	0.8456
North-Eastern	0.8083	0.8938	0.9335	0.9480	0.8946	0.8024	0.8895	0.9296	0.9449	0.8902	0.7992	0.8866	0.9281	0.9441	0.8881
Central	0.8646	0.8867	0.9038	0.9023	0.8894	0.8617	0.8846	0.9016	0.9000	0.8870	0.8614	0.8844	0.9021	0.9018	0.8894
Southern	0.5996	0.6446	0.6986	0.7218	0.6662	0.5969	0.6419	0.6956	0.7191	0.6633	0.5968	0.6423	0.6971	0.7208	0.6643

Notes:
In model A, ME, FPS, MK, YEAR_FOUND, WOMEN and GDP have been used as determinants of inefficiency; In model B, ME, FPS, MK, YEAR_FOUND, WOMEN and FD_1 have been used as determinants of inefficiency; In model C, ME, FPS, MK, YEAR_FOUND, WOMEN and FD_2 have been used as determinants of inefficiency.

among all the years.

When looking, instead, at the parametric estimates (SFA efficiency scores), it is even more clear than the universities located in the Central-North area perform better than those in the Southern area as now around 86% of the universities with a level of efficiency over the sample mean are located in the Central-North area (the mean efficiency of all universities is 0.7023, considering Model A in Table 6), when a Cobb-Douglas production function has been considered. When we consider the big city areas where many universities are located, the Rome area is particularly efficient with an average efficiency of 0.8728, the Milan area also shows good performances with an average of 0.8713 and the Naples area shows lower performances with an average of 0.6418 among all the years. When instead the Translog production function has been take into account, around 74% of the universities with a level of efficiency over the sample mean are located in the Central-North area (the mean efficiency of all universities is 0.8043, considering Model A in Table 6). The Rome area is particularly efficient with an average efficiency of 0.9522, the Milan area also shows good performances with an average of 0.9466 and the Naples area shows lower performances with an average of 0.7361 among all the years.

The main differences among the two estimation methods employed in the paper regard the university rankings (see Table 7, below). Indeed, looking for instance at the universities ranked in the first 10 position, 8 of them - Università degli Studi "Cà Foscari" – Venezia, Università degli Studi di Genova, Università degli Studi di Roma Tre, Università degli Studi Gabriele D'Annunzio - Chieti e Pescara (when using DEA), and - Università degli Studi "La Sapienza" – Roma, Università degli Studi di Firenze, Università degli Studi di Pisa, Università degli Studi "Federico II" – Napoli (when using SFA with a Cobb-Douglas production function), are present only in one of the rankings; instead, only few of them (Politecnico di Milano, Università degli Studi di Padova, Università degli Studi di Bologna, Università degli Studi di Milano, Università degli Studi di Siena, Università degli Studi di Torino) are present in both rankings. Among them, only one of the universities (Università degli Studi di Milano) assumes the same position (6th) confronting DEA and SFA (with a Cobb-Douglas production function). While all the other universities present in both rankings, are positioned differently. Similar findings have also been found at the bottom of the ranking where only 5 institutions are confirmed in last 10 position of the ranking when the two estimation methods are compared. Relevant differences persist when confronting the DEA approach and the SFA when a Translog production function has been assumed when relating inputs and outputs in the stochastic frontier analysis; indeed, still looking at the universities ranked in the first 10 position, 10 of them - Università degli Studi "Cà Foscari" – Venezia, Università degli Studi di Milano, Università degli Studi di Siena, Università degli Studi di Roma Tre, Università degli Studi Gabriele D'Annunzio – Chieti/Pescara (when using DEA), and - Università degli Studi "La Sapienza" – Roma, Università degli Studi di Firenze, Università degli Studi "Federico II" – Napoli, Università degli Studi di Pisa, Università degli Studi di Bari (when using SFA with a Translog production function), are present only in one of the rankings; instead, only few of them (Politecnico di Milano, Università degli Studi di Padova, Università degli Studi di Genova, Università degli Studi di Bologna, Università degli Studi di Torino) are present in both rankings. More similar are, instead, the rankings produced by the two SFA methods (with a Cobb-Douglas and a Translog production function), as 8 out of 10 universities ranked in the first 10 positions are presents in both rankings; among them, two institutions, such as Università degli Studi "La Sapienza" – Roma and Università degli Studi di Bologna, assume the same position (1st and 2nd).

These results are furthermore confirmed by the scatter plot in Figs. 1 and 2 below which shows that the different methods do not identify a common set of universities at the top and at the bottom ends of performances, differently from what has been found by Johnes [10] who instead found a common (but very small) group of high and low performing institutions. Similarly to the Johnes [10]; results show that probably the ranking of middle performing universities are less informative.

Boxplots and Kernel distributions of efficiency scores (pooling all years) are presented in Figs. 3 and 4 below. Differences between

Table 6
DEA technical efficiency and SFA directional output distance efficiency scores over the period 2008–2011 by university.

		DEA efficiency scores			SFA efficiency scores			SFA efficiency scores		
					Cobb-Douglas			Translog		
		(No boot)	(Boot)	(Bias)	(A)	(B)	(C)	(A)	(B)	(C)
1	Università Politecnica delle Marche- Ancona	0.8135	0.7548	0.0587	0.6771	0.8014	0.6605	0.8009	0.7946	0.7985
2	Università della Calabria - Arcavacata di Rende	0.6642	0.6068	0.0574	0.5872	0.6670	0.5714	0.8152	0.8174	0.8231
3	Politecnico di Bari	0.6348	0.5654	0.0694	0.4452	0.5280	0.4395	0.4746	0.4702	0.4718
4	Università degli Studi di Bari	0.8164	0.7408	0.0756	0.7459	0.8421	0.7342	0.9646	0.9648	0.9654
5	Università degli Studi del Sannio - Benevento	0.6157	0.4544	0.1613	0.4224	0.5072	0.4139	0.4063	0.4005	0.4007
6	Università degli Studi di Bergamo	1.0000	0.7161	0.2839	0.6033	0.7030	0.5898	0.6916	0.6887	0.6924
7	Università degli Studi di Bologna	1.0000	0.8306	0.1694	0.9735	0.9880	0.9718	0.9880	0.9880	0.9887
8	Università degli Studi di Brescia	0.5669	0.5226	0.0443	0.5742	0.6741	0.5649	0.6779	0.6751	0.6752
9	Università degli Studi di Cagliari	0.7890	0.7088	0.0802	0.6890	0.7801	0.6825	0.8482	0.8481	0.8476
10	Università degli Studi del Molise - Campobasso	0.8725	0.7076	0.1649	0.5063	0.5768	0.4998	0.5881	0.5825	0.5812
11	Università degli Studi di Cassino	0.7834	0.6092	0.1742	0.5378	0.6680	0.5226	0.6047	0.5996	0.5983
12	Università degli studi di Catania	0.7980	0.7080	0.0900	0.7461	0.8467	0.7325	0.9535	0.9543	0.9555
13	Università degli Studi “Magna Grecia” - Catanzaro	0.8080	0.6973	0.1107	0.4988	0.5612	0.4897	0.5385	0.5344	0.5374
14	Università degli Studi Gabriele D'Annunzio — Chieti/Pescara	0.9097	0.7727	0.1370	0.6729	0.7574	0.6670	0.9077	0.9086	0.9097
15	Università degli Studi di Ferrara	0.6677	0.6149	0.0528	0.6623	0.7534	0.6531	0.8214	0.8146	0.8108
16	Università degli Studi di Firenze	1.0000	0.7585	0.2415	0.9577	0.9876	0.9527	0.9807	0.9805	0.9809
17	Università degli Studi di Foggia	0.6259	0.5760	0.0499	0.4862	0.5361	0.4797	0.5252	0.5204	0.5212
18	Università degli Studi di Genova	0.9286	0.8375	0.0911	0.8480	0.9453	0.8519	0.9643	0.9626	0.9609
19	Università del Salento - Lecce	0.8436	0.7703	0.0733	0.6417	0.6777	0.6313	0.8906	0.8890	0.8904
20	Università degli Studi di Messina	0.6694	0.6137	0.0557	0.6576	0.7336	0.6459	0.7886	0.7899	0.7908
21	Politecnico di Milano	0.9544	0.8850	0.0694	0.9172	0.9905	0.9134	0.9678	0.9682	0.9686
22	Università degli Studi di Milano	0.9575	0.8129	0.1446	0.9408	0.9921	0.9363	0.9633	0.9635	0.9640
23	Università degli Studi - Milano-Bicocca	0.8112	0.7291	0.0821	0.7559	0.9845	0.7503	0.9087	0.9092	0.9104
24	Università degli Studi di Modena e Reggio Emilia	0.6802	0.6164	0.0638	0.7053	0.8300	0.6941	0.7896	0.7836	0.7799
25	Seconda Università degli studi di Napoli	0.6210	0.5707	0.0503	0.6090	0.7286	0.6066	0.7571	0.7550	0.7542
26	Università degli Studi “Federico II” - Napoli	0.8058	0.7035	0.1023	0.8700	0.9657	0.8636	0.9671	0.9670	0.9670
27	Università degli Studi “L' Orientale” - Napoli	0.9837	0.7639	0.2198	0.6292	0.7271	0.6251	0.7161	0.7107	0.7124
28	Università degli Studi “Parthenope” - Napoli	0.6246	0.5479	0.0767	0.4593	0.5877	0.4553	0.5044	0.5031	0.5022
29	Università degli Studi di Padova	0.9380	0.8504	0.0876	0.9481	0.9788	0.9413	0.9783	0.9783	0.9783
30	Università degli Studi - Palermo	0.8431	0.7391	0.1040	0.7584	0.8363	0.7480	0.9589	0.9587	0.9605
31	Università degli Studi di Parma	0.7091	0.6557	0.0534	0.7563	0.8733	0.7454	0.9124	0.9093	0.9065
32	Università degli Studi di Pavia	0.8219	0.7440	0.0779	0.7882	0.8646	0.7787	0.8983	0.8981	0.8983
33	Università degli Studi di Perugia	0.7972	0.7358	0.0614	0.8151	0.9376	0.8030	0.9224	0.9192	0.9215
34	Università degli Studi di Pisa	0.8051	0.7219	0.0832	0.8841	0.9677	0.8651	0.9664	0.9661	0.9670
35	Università degli Studi della Basilicata - Potenza	0.9119	0.6522	0.2597	0.4512	0.5213	0.4409	0.5049	0.5006	0.4994
36	Università degli Studi Mediterranea - Reggio Calabria	0.5158	0.4451	0.0707	0.4558	0.5421	0.4453	0.4906	0.4860	0.4874
37	Università degli Studi di Roma Tre	0.8849	0.8092	0.0757	0.8317	0.9846	0.8329	0.9535	0.9533	0.9528
38	Università degli Studi “La Sapienza” - Roma	1.0000	0.6854	0.3146	0.9827	0.9942	0.9829	0.9899	0.9898	0.9898
39	Università degli Studi di “Tor Vergata” - Roma	0.7936	0.7367	0.0569	0.8041	0.9814	0.8100	0.9132	0.9127	0.9114
40	Università degli Studi di Salerno	0.5799	0.5302	0.0497	0.5586	0.6503	0.5489	0.7177	0.7158	0.7158
41	Università degli Studi di Sassari	0.6374	0.5757	0.0617	0.5819	0.6623	0.5734	0.6209	0.6199	0.6194
42	Università degli Studi di Siena	1.0000	0.8128	0.1872	0.9430	0.9738	0.9380	0.9498	0.9487	0.9517
43	Università degli Studi di Teramo	1.0000	0.6816	0.3184	0.4638	0.5430	0.4552	0.5561	0.5509	0.5530
44	Politecnico di Torino	0.8202	0.7294	0.0908	0.7161	0.8562	0.7104	0.8812	0.8806	0.8758
45	Università degli Studi di Torino	0.9000	0.7823	0.1177	0.9377	0.9809	0.9337	0.9809	0.9808	0.9805
46	Università degli Studi - Trieste	0.8302	0.7483	0.0819	0.7739	0.8364	0.7697	0.9225	0.9181	0.9140
47	Università degli Studi - Udine	0.6904	0.6242	0.0662	0.7134	0.8669	0.7066	0.8319	0.8250	0.8196
48	Università dell' Insubria - Varese	0.6787	0.5866	0.0921	0.6200	0.7247	0.6090	0.6987	0.6950	0.6962
49	Venezia - Università IUAV	1.0000	0.6733	0.3267	0.8148	0.8878	0.8039	0.8397	0.8289	0.8284
50	Università degli Studi “Cà Foscari” - Venezia	0.9321	0.8446	0.0875	0.8106	0.8906	0.7975	0.9490	0.9468	0.9467
51	Università degli Studi del Piemonte orientale “A. Avogadro”	0.6026	0.5250	0.0776	0.5601	0.6252	0.5538	0.6819	0.6777	0.6789
52	Università degli Studi di Verona	0.7625	0.6946	0.0679	0.7268	0.8513	0.7162	0.8866	0.8833	0.8818
53	Università della Tuscia - Viterbo	1.0000	0.6974	0.3026	0.7101	0.7988	0.6941	0.8121	0.8052	0.8022

Notes:
No boot refer to the estimates of DEA efficiency scores not-bootstrapped in the first stage. Boot report estimates of DEA efficiency scores bootstrapped in the first stage. Bias refers to the bias found in the estimation.
In model A, MED, FPS, MK, YEAR_FOUND, WOMEN and GDP have been used as inputs; in model B, ME, FPS, MK, YEAR_FOUND, WOMEN and FD_1 have been used as inputs; in model C, MED, FPS, MK, YEAR_FOUND, WOMEN and FD_2 have been used as inputs.

efficiencies of universities not only in the mean, but also in the distribution is shown through the boxplots; considering the Kernel distributions, the universities are more efficient, the closer they come to the value of one. North-Central regions of the country are characterized by a skewed distribution with more concentration in the direction of more efficient units; moreover, comparing biased (non-bootstrapped) and unbiased (bootstrapped) efficiency scores, it's clear that the distribution of the latter one are slightly on the left indicating lower level of efficiency scores.

4.2. (In)efficiency score determinants

When considering the exogenous factors included in the analysis, our findings show that the variables used to control for the different competitive environment in which institutions are located, have an important role in describing the inefficiency term. In both DEA and SFA formulations, a positive sign of the estimated regression parameter indicates that, ceteris paribus, an increase in a variable corresponds to higher inefficiency (lower efficiency), while

Table 7
DEA and SFA technical efficiency over the period 2008 2011 by university — Ranking of universities.

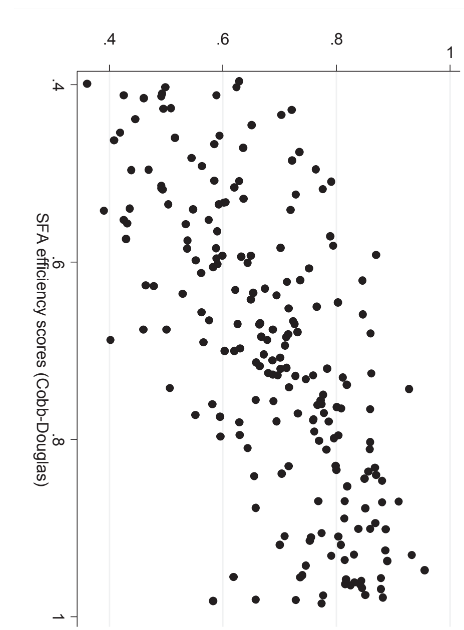
N.	Universities	DEA	N.	Universities	SFA (A) Cobb Douglas	N.	Universities	SFA (A) Translog
1	Politecnico di Milano	0.885	1	Università degli Studi "La Sapienza" - Roma	0.982	1	Università degli Studi "La Sapienza" - Roma	0.989
2	Università degli Studi di Padova	0.850	2	Università degli Studi di Bologna	0.973	2	Università degli Studi di Bologna	0.988
3	Università degli Studi "Cà Foscari" - Venezia	0.844	3	Università degli Studi di Firenze	0.957	3	Università degli Studi di Torino	0.980
4	Università degli Studi di Genova	0.837	4	Università degli Studi di Padova	0.948	4	Università degli Studi di Firenze	0.980
5	Università degli Studi di Bologna	0.830	5	Università degli Studi di Siena	0.943	5	Università degli Studi di Padova	0.978
6	Università degli Studi di Milano	0.812	6	Università degli Studi di Milano	0.940	6	Politecnico di Milano	0.967
7	Università degli Studi di Siena	0.812	7	Università degli Studi di Torino	0.937	7	Università degli Studi "Federico II" - Napoli	0.967
8	Università degli Studi di Roma Tre	0.809	8	Politecnico di Milano	0.917	8	Università degli Studi di Pisa	0.966
9	Università degli Studi di Torino	0.782	9	Università degli Studi di Pisa	0.884	9	Università degli Studi di Bari	0.964
10	Università degli Studi Gabriele D'Annunzio - Chieti e Pescara	0.772	10	Università degli Studi "Federico II" - Napoli	0.870	10	Università degli Studi di Genova	0.964
11	Università del Salento - Lecce	0.770	11	Università degli Studi di Genova	0.848	11	Università degli Studi di Milano	0.963
12	Università degli Studi "L' Orientale" - Napoli	0.763	12	Università degli Studi di Roma Tre	0.831	12	Università degli Studi - Palermo	0.958
13	Università degli Studi di Firenze	0.758	13	Università degli Studi di Perugia	0.815	13	Università degli studi di Catania	0.953
14	Università Politecnica delle Marche- Ancona	0.754	14	Venezia - Università IUAV	0.814	14	Università degli Studi di Roma Tre	0.953
15	Università degli Studi - Trieste	0.748	15	Università degli Studi "Cà Foscari" - Venezia	0.810	15	Università degli Studi di Siena	0.949
16	Università degli Studi di Pavia	0.744	16	Università degli Studi di "Tor Vergata" - Roma	0.804	16	Università degli Studi "Cà Foscari" - Venezia	0.949
17	Università degli Studi di Bari	0.740	17	Università degli Studi di Pavia	0.788	17	Università degli Studi - Trieste	0.922
18	Università degli Studi - Palermo	0.739	18	Università degli Studi - Trieste	0.773	18	Università degli Studi di Perugia	0.922
19	Università degli Studi di "Tor Vergata" - Roma	0.736	19	Università degli Studi - Palermo	0.758	19	Università degli Studi di "Tor Vergata" - Roma	0.913
20	Università degli Studi di Perugia	0.735	20	Università degli Studi di Parma	0.756	20	Università degli Studi di Parma	0.912
21	Politecnico di Torino	0.729	21	Università degli Studi - Milano-Bicocca	0.755	21	Università degli Studi - Milano-Bicocca	0.908
22	Università degli Studi - Milano-Bicocca	0.729	22	Università degli studi di Catania	0.746	22	Università degli Studi Gabriele D'Annunzio — Chieti/Pescara	0.907
23	Università degli Studi di Pisa	0.721	23	Università degli Studi di Bari	0.745	23	Università degli Studi di Pavia	0.898
24	Università degli Studi di Bergamo	0.716	24	Università degli Studi di Verona	0.726	24	Università del Salento - Lecce	0.890
25	Università degli Studi di Cagliari	0.708	25	Politecnico di Torino	0.716	25	Università degli Studi di Verona	0.886
26	Università degli studi di Catania	0.708	26	Università degli Studi - Udine	0.713	26	Politecnico di Torino	0.881
27	Università degli Studi del Molise - Campobasso	0.707	27	Università della Tuscia - Viterbo	0.710	27	Università degli Studi di Cagliari	0.848
28	Università degli Studi "Federico II" - Napoli	0.703	28	Università degli Studi di Modena e Reggio Emilia	0.705	28	Venezia - Università IUAV	0.839
29	Università della Tuscia - Viterbo	0.697	29	Università degli Studi di Cagliari	0.689	29	Università degli Studi - Udine	0.831
30	Università degli Studi "Magna Grecia" - Catanzaro	0.697	30	Università Politecnica delle Marche- Ancona	0.677	30	Università degli Studi di Ferrara	0.821
31	Università degli Studi di Verona	0.694	31	Università degli Studi Gabriele D'Annunzio — Chieti/Pescara	0.672	31	Università della Calabria - Arcavacata di Rende	0.815
32	Università degli Studi "La Sapienza" - Roma	0.685	32	Università degli Studi di Ferrara	0.662	32	Università della Tuscia - Viterbo	0.812
33	Università degli Studi di Teramo	0.681	33	Università degli Studi di Messina	0.657	33	Università Politecnica delle Marche- Ancona	0.800
34	Venezia - Università IUAV	0.673	34	Università del Salento - Lecce	0.641	34	Università degli Studi di Modena e Reggio Emilia	0.789
35	Università degli Studi di Parma	0.655	35	Università degli Studi "L' Orientale" - Napoli	0.629	35	Università degli Studi di Messina	0.788
36	Università degli Studi della Basilicata - Potenza	0.652	36	Università dell'Insubria - Varese	0.620	36	Seconda Università degli studi di Napoli	0.757
37	Università degli Studi - Udine	0.624	37	Seconda Università degli studi di Napoli	0.609	37	Università degli Studi di Salerno	0.717
38	Università degli Studi di Modena e Reggio Emilia	0.616	38	Università degli Studi di Bergamo	0.603	38	Università degli Studi "L' Orientale" - Napoli	0.716
39	Università degli Studi di Ferrara	0.614	39	Università della Calabria - Arcavacata di Rende	0.587	39	Università dell'Insubria - Varese	0.698
40	Università degli Studi di Messina	0.613	40	Università degli Studi di Sassari	0.581	40	Università degli Studi di Bergamo	0.691
41	Università degli Studi di Cassino	0.609	41	Università degli Studi di Brescia	0.574	41		0.681

(*continued on next page*)

Table 7 (*continued*)

N.	Universities	DEA	N.	Universities	SFA (A) Cobb Douglas	N.	Universities	SFA (A) Translog
							Università degli Studi del Piemonte orientale "A. Avogadro"	
42	Università della Calabria - Arcavacata di Rende	0.606	42	Università degli Studi del Piemonte orientale "A. Avogadro"	0.560	42	Università degli Studi di Brescia	0.677
43	Università dell' Insubria - Varese	0.586	43	Università degli Studi di Salerno	0.558	43	Università degli Studi di Sassari	0.620
44	Università degli Studi di Foggia	0.576	44	Università degli Studi di Cassino	0.537	44	Università degli Studi di Cassino	0.604
45	Università degli Studi di Sassari	0.575	45	Università degli Studi del Molise - Campobasso	0.506	45	Università degli Studi del Molise - Campobasso	0.588
46	Seconda Università degli studi di Napoli	0.570	46	Università degli Studi "Magna Grecia" - Catanzaro	0.498	46	Università degli Studi di Teramo	0.556
47	Politecnico di Bari	0.565	47	Università degli Studi di Foggia	0.486	47	Università degli Studi "Magna Grecia" - Catanzaro	0.538
48	Università degli Studi "Parthenope" - Napoli	0.547	48	Università degli Studi di Teramo	0.463	48	Università degli Studi di Foggia	0.525
49	Università degli Studi di Salerno	0.530	49	Università degli Studi "Parthenope" - Napoli	0.459	49	Università degli Studi della Basilicata — Potenza	0.504
50	Università degli Studi del Piemonte orientale "A. Avogadro"	0.525	50	Università degli Studi Mediterranea - Reggio Calabria	0.455	50	Università degli Studi "Parthenope" - Napoli	0.504
51	Università degli Studi di Brescia	0.522	51	Università degli Studi della Basilicata — Potenza	0.451	51	Università degli Studi Mediterranea - Reggio Calabria	0.490
52	Università degli Studi del Sannio - Benevento	0.454	52	Politecnico di Bari	0.445	52	Politecnico di Bari	0.474
53	Università degli Studi Mediterranea - Reggio Calabria	0.445	53	Università degli Studi del Sannio - Benevento	0.422	53	Università degli Studi del Sannio - Benevento	0.406

Notes: DEA: Estimates of DEA efficiency scores bootstrapped in the first stage are reported; SFA: MED, FPS, MK, YEAR_FOUND, WOMEN and GDP have been used as outputs.

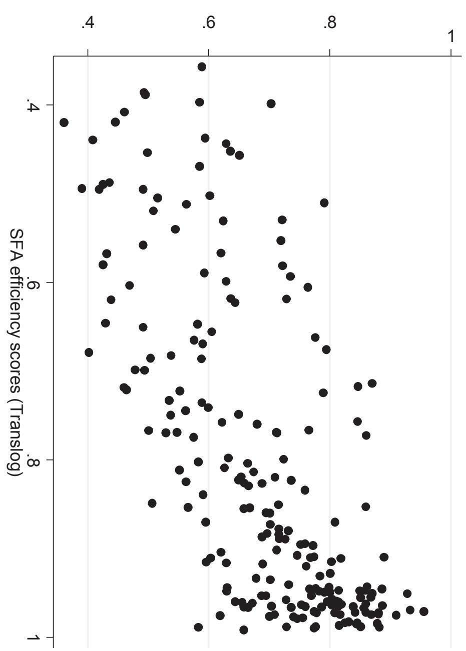


Note: A low rank implies a low performance

Fig. 1. Scatter plot of rankings. Note: A low rank implies a low performance.

a negative sign of estimated parameter indicates lower inefficiency (greater efficiency). Due to space constraints, the list of estimated coefficients, discussed below, is reported in the Online Appendix (Tables 8–11).

Specifically, we found a positive and significant coefficient, which indicates a lower efficiency, for universities with regards to the medical faculty (MED); as already specified by Curi et al. [20]; the empirical evidence on whether the presence of medical schools make universities more or less efficient is controversial, and the "differences in results might be due to the different production process characterizations in the different models". Our findings are consistent with the studies by Thursby and Kemp [81]; Anderson et al. [82] and Chapple et al. [83] who show that the presence of a medical school reduces the efficiency level, probably due to the heavy service commitments of medical schools or to differences in the health product market. We also find a negative and statistically significant coefficient on the fees per student variable (FPS); this indicates that the higher levels of fees per capita are associated with higher levels of universities' efficiency. This finding is also consistent with the interpretation that when market forces operate, there are benefits for HEIs' efficiency — an analogous finding about the



Note: A low rank implies a low performance

Fig. 2. Scatter plot of rankings. Note: A low rank implies a low performance.

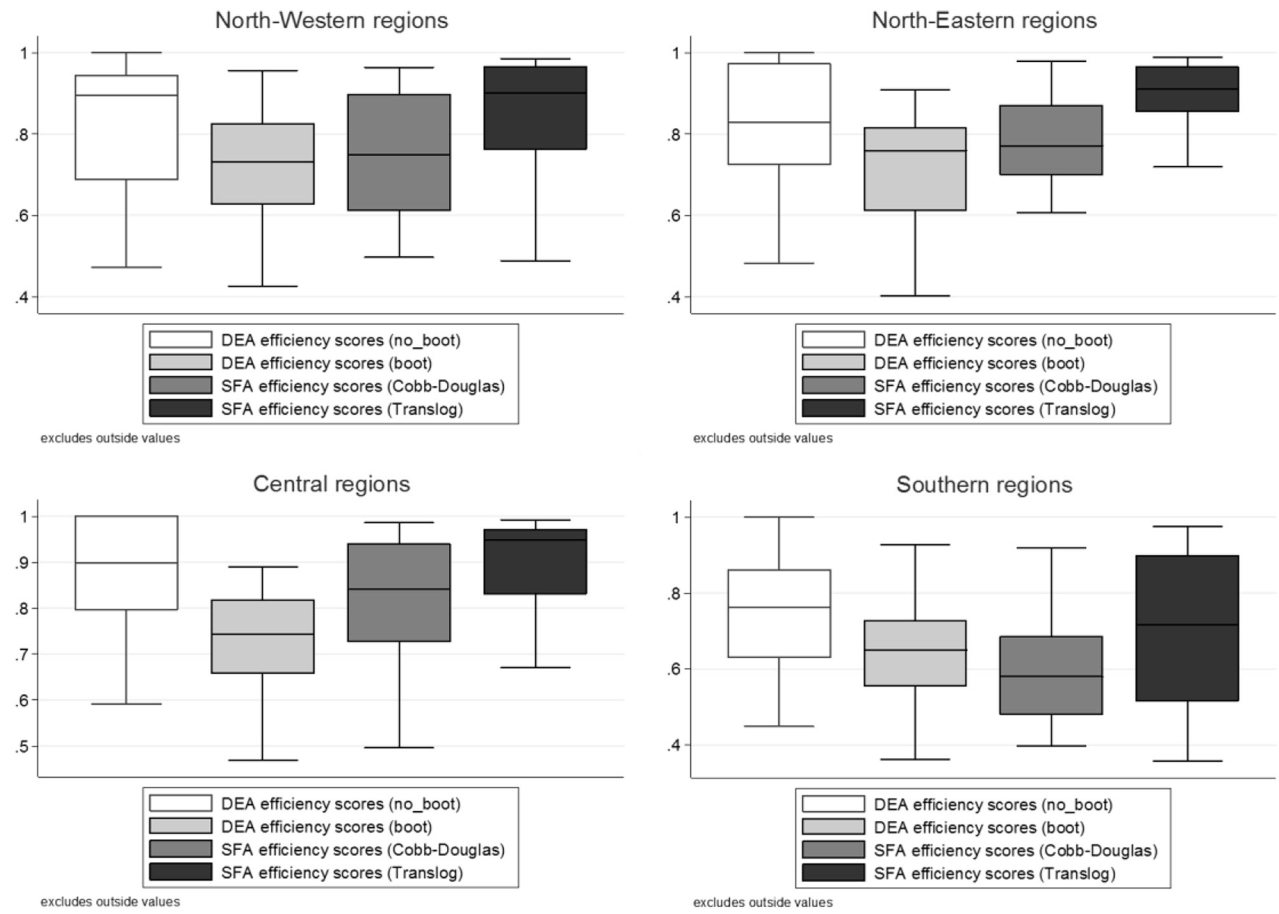


Fig. 3. Boxplots efficiency scores.

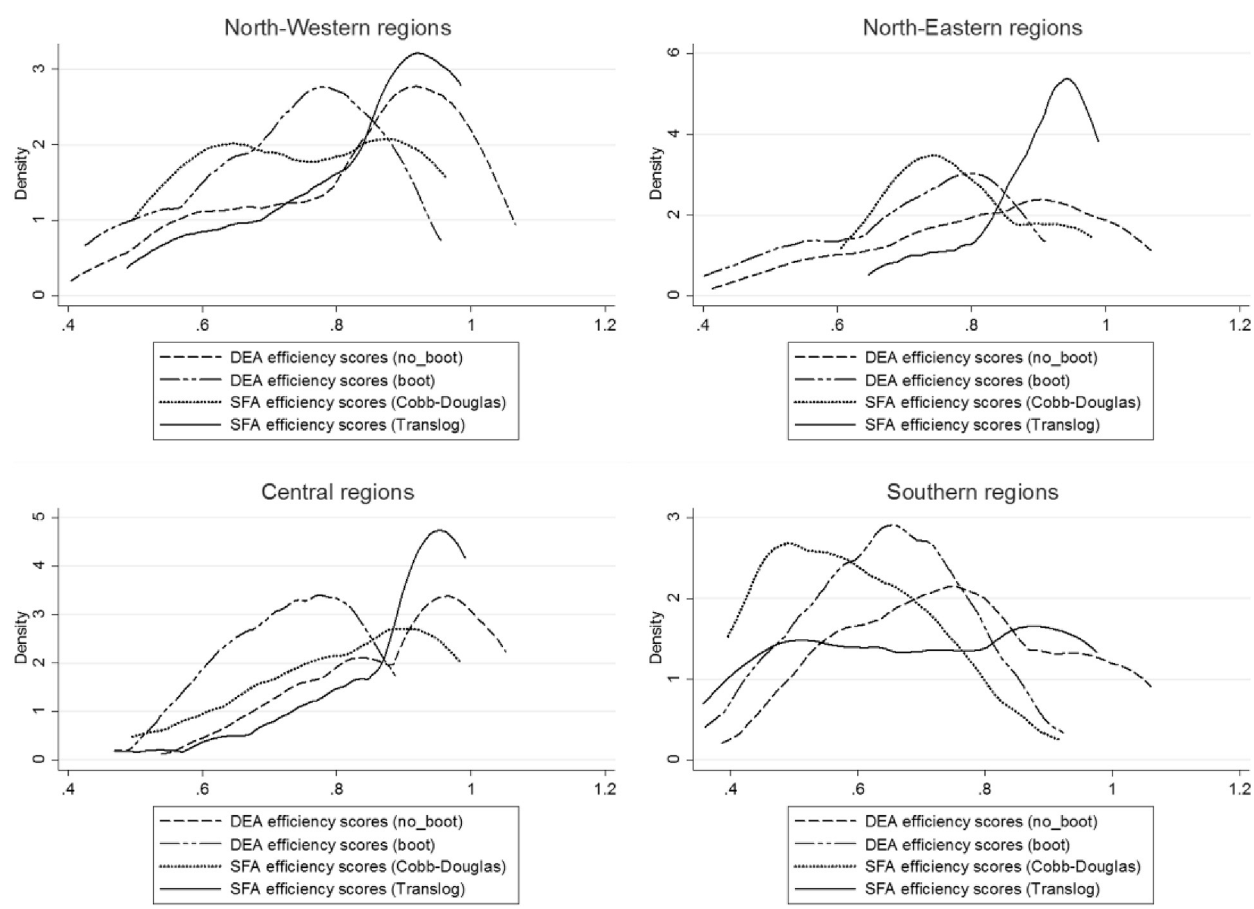


Fig. 4. Kernel density estimates.

positive association between efficiency and fees of Italian universities is in Agasisti et al. [45] and Agasisti and Wolszczak-Derlacz [84]. Moreover, inefficiency has a U-shaped relationship with respect to the measure of market competition (MK), showing a negative and statistically significant relationship between inefficiency and market share while, instead, a positive and statistically significant relationship between inefficiency and (squared) market share has been found. In other words, the increase in concentration does not lead to a linear change in efficiency; at some point, the effect becomes positive, and the quadratic shape means that the inefficiency of HEIs with respect to the measure of market concentration is increasing as concentration increases (i.e. universities are less efficient), and the results can be due to the finishing incentives in becoming efficient when concentration arises indeed. This is only one of the channel through which the market structure might play a role as our measure of competition is specifically build on the geographical proximity among universities within the region; however, this is an interesting portion of competition effect as Italian students tend to choose a university located in their own region, despite the Italian university system offers different quality standards, due to family income constraint (on this point see Ref. [85]). Overall, these findings suggest that differences in performances might be due to the market structure of higher education, in the direction that a more competitive environment could lead to higher efficiency, consistently with Agasisti et al. [45]; Agasisti [75] and Rossi [86]. The estimation results reveal that the coefficient associated with the presence of female students (WOMEN) is, in general, negative and statistically significant, meaning that the higher is the share of females among the students the higher is the efficiency of the universities. A negative and statistically significant coefficient has been found on the variable gross domestic product (GDP), and on the financial progress variables (FD_1 and FD_2), which means that operating in more economically developed areas is associated, on average, with higher efficiency. Finally, results show that younger universities (YEAR_FOND) are less efficient.

5. Conclusions

In this paper we have attempted to analysis the efficiency of Italian higher education using both parametric and non-parametric methods with the aim of providing guidance to university managers and policymakers on the sensitivity of the results to the technique used. To do this, we firstly employ both a double-bootstrap procedure and a two-stage bootstrap Data Envelopment Analysis (DEA), to generate unbiased coefficients [18] and then a Stochastic Frontier Analysis (SFA both with a Cobb-Douglas and a Translog production function), modelling the production set through an output distance function, applying a within transformation to data as developed by Wang and Ho [23]; exogenous factors, such as some institutional details and characteristics of the market place and of the regions where the universities are located, have been also taken into account to evaluate which determinants have an impact on universities' efficiencies.

Firstly, the findings suggest the presence of some geographical effects with institutions located in the Central-North area showing higher efficiency scores than those in the Southern area, with both the empirical approaches. This result is in line with the idea that universities need guidelines to follow in order to avoid waste of public funding; indeed, a debate is emerging about the weakened role of universities in Italy, due to the cut in public funding. Particularly in weak areas, like those of the South of Italy, where the main producer of knowledge is public university, the effect of linking public funding to performance could also produce negative cumulative effects: for example, students may prefer universities in the North of Italy, thus destroying the possibility of local knowledge spillovers [87,88]. More specifically, when apply a bootstrapping method in contrast to straightforward application of DEA (in order to investigate the sensibility of efficiency scores relative to the sampling variations of the estimated frontier and thus obtain bias corrected efficiency estimates) the empirical evidence shows that the efficiency scores calculated without bootstrap might be overestimated suggesting the importance of using a bootstrapped DEA approach.

Secondly, results show that, on average, the level of efficiency does not significantly change among estimation methods, but at the same time they produce different rankings (especially when confronting DEA and SFA models). Indeed, looking at the universities ranked in the first 10 positions, most of them are present only in one of the rankings; instead, only few of them are present in both. Moreover, only one of the universities assumes the same position, while all the other universities present in both rankings, are positioned differently. Those differences are confirmed among the low performing universities, implying that the two methods may be able to provide useful information more at the top and bottom of the performances, being instead less informative in the middle, as the evidence shows that they do not identify a common set of high and low performing institutions. Interestingly, different rankings are produced mainly between estimation methods such as DEA versus SFA (both with a Cobb-Douglas and a Translog production function). Assumption on the functional forms are less informative as the league tables produced within the same estimation method (SFA with a Cobb-Douglas and a Translog production function) are, instead, more similar. In other words, the methods of analysis employed do matter when ranking universities, suggesting that university rankings should be handled with extreme caution.

Thirdly, at the second stage of our analysis, we linked the technical efficiency scores of single HEIs with variables describing their location, the institution, year of foundation and some characteristics of the marketplace; interestingly, the results show that inefficiency is U-shaped relationship with respect to the measure of market competition in favor of a more competitive environment in order to reach higher efficiency and that the higher is the level of fees per capita the lower is the universities' inefficiency. All findings that provide a clue towards the expansion of pro-competitive policies in the Italian higher education sector, consistently with the interpretation that when market forces operate, there are benefits for university efficiency, pointing at a development of a quasi-market in the provision of education where students are free to choose the university to attend and institutions are allowed to compete for students.

To conclude, the lesson learned suggests that policymakers should be aware that the estimates of the level of efficiency could vary by estimation methods and, more importantly, that the ranking of universities may change as ineffective decisions might be driven from potential diverging results and in case no consensus emerge on the group of high and low performing institutions rated; indeed, in other words, university managers may be appealed, in order to improve their ranking, attract more students and obtain more funding, to rely on the most appropriate method for their needs and that best reflects their own preferences. As both human and financial resources and decisions might depend on how the universities are positioned in such classifications, it is useful to providing further light on the delicate processes of evaluating the efficiency of HEIs. The lack of empirical evidence in the literature about the proximity of these two approaches in measuring technical efficiency of higher education calls into question the need of providing new evidence regarding the success of efficiency analyses in producing reliable and consistent estimates and, more importantly, rankings of institutions, which are not sensitive to the specification of the technique used to produce the efficiency scores.

APPENDIX

Table 8
DEA truncated bootstrapped second stage regression.

	Min-Max Truncation - UB = 0.64 & LB = 0.04			Min-Max Truncation - UB = 0.90 & LB = 0.40		
	BOOT			NO-BOOT		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
MED	0.058** (0.023)	0.063*** (0.015)	0.062*** (0.017)	0.154*** (0.029)	0.158*** (0.028)	0.158*** (0.031)
FPS	−0.0001*** (0.00003)	−0.0001*** (0.00003)	−0.0001*** (0.00003)	−0.0001*** (0.00005)	−0.0009*** (0.00003)	−0.0002*** (0.00004)
MK	−0.505*** (0.157)	−0.464*** (0.143)	−0.479*** (0.132)	−0.259 (0.206)	−0.210 (0.171)	−0.214 (0.248)
MK^2	0.319** (0.141)	0.299** (0.126)	0.313** (0.125)	0.018 (0.199)	−0.006 (0.166)	−0.003 (0.235)
YEAR_FOND	0.00007** (0.00002)	0.00006** (0.00003)	0.00005* (0.00003)	0.00006 (0.00005)	0.00006 (0.00004)	0.00005 (0.00005)
WOMEN	4.62e-07 (1.17e-06)	−4.25e-08 (1.23e-06)	−9.40e-08 (1.06e-06)	−3.57e-06** (1.53e-06)	−3.96e-06*** (1.37e-06)	−4.25e-06** (1.32e-06)
GDP	−9.49e-07*** (2.32e-07)			−1.06e-06* (6.35e-07)		
FD_1		−0.0007*** (0.0002)			−0.0009*** (0.0003)	
FD_2			−0.001*** (0.0004)			−0.001 (0.0008)
NORTHERN	−0.010 (0.024)	−0.016 (0.023)	−0.014 (0.022)	−0.011 (0.048)	−0.015 (0.048)	−0.017 (0.036)
CENTRAL	−0.038 (0.026)	−0.042* (0.024)	−0.040** (0.018)	−0.072 (0.044)	−0.073* (0.041)	−0.075* (0.043)
T2	−0.020 (0.022)	−0.019 (0.019)	−0.019 (0.020)	−0.002 (0.032)	−0.001 (0.028)	−0.001 (0.031)
T3	−0.107*** (0.025)	−0.108*** (0.022)	−0.107*** (0.022)	−0.065** (0.034)	−0.066* (0.036)	−0.065** (0.028)
T4	−0.156*** (0.025)	−0.157*** (0.020)	−0.155*** (0.023)	−0.100*** (0.035)	−0.100*** (0.032)	−0.099*** (0.030)
CONST	0.449*** (0.070)	0.449*** (0.085)	0.481*** (0.076)	0.359*** (0.127)	0.348*** (0.108)	0.384*** (0.121)

Table reports coefficients and standard error (in parentheses); ***, **, *: statistically significant al 1%, 5% and 10% respectively.
Columns (1), (2) and (3) are associated with bootstrapped university efficiency scores in the first stage (Double-boot DEA procedure).
Columns (4), (5) and (6) are associated with not bootstrapped university efficiency scores in the first stage (Two-stage DEA procedure).

Table 9
DEA truncated bootstrapped second stage regression using quartile university efficiency scores.

	Min-Max Truncation - UB = 0.64 & LB = 0.04			Min-Max Truncation - UB = 0.64 & LB = 0.04			Min-Max Truncation - UB = 0.64 & LB = 0.04		
	Without the 1st quartile			Without the 4th quartile			Without the 1st and the 4th quartiles		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MED	0.059*** (0.020)	0.064*** (0.021)	0.063** (0.024)	0.070** (0.028)	0.077*** (0.028)	0.076*** (0.028)	0.078*** (0.027)	0.085*** (0.030)	0.083** (0.035)
FPS	−0.0001*** (0.00004)	−0.0001*** (0.00003)	−0.0001*** (0.00003)	−0.00009* (0.00005)	−0.0008** (0.00004)	−0.0001* (0.00005)	−0.0001** (0.00005)	−0.0001*** (0.00004)	−0.0001* (0.00007)
MK	−0.450** (0.176)	−0.416*** (0.122)	−0.429*** (0.136)	−0.625*** (0.205)	−0.566** (0.255)	−0.584*** (0.210)	−0.635*** (0.224)	−0.586** (0.246)	−0.605** (0.259)
MK^2	0.296* (0.158)	0.280** (0.112)	0.291** (0.120)	0.427** (0.181)	0.398* (0.238)	0.413** (0.189)	0.466** (0.196)	0.443** (0.220)	0.459* (0.236)
YEAR_FOND	0.00006* (0.00003)	0.00006* (0.00003)	0.00005* (0.00003)	0.00007 (0.00004)	0.00007* (0.00004)	0.00005 (0.00004)	0.00007 (0.00005)	0.00007 (0.00005)	0.00006 (0.00006)
WOMEN	8.74e-07 (1.32e-06)	5.05e-07 (8.63e-07)	4.43e-07 (1.08e-06)	−2.52e-07 (1.93e-06)	−9.50e-07 (2.05e-06)	−1.05e-06 (1.91e-06)	7.48e-07 (1.80e-06)	2.34e-07 (1.72e-06)	9.67e-08 (1.57e-06)
GDP	−7.97e-07*** (2.26e-07)			−1.41e-06*** (4.87e-07)			−1.22e-06*** (5.51e-07)		
FD_1		−0.0006*** (0.0002)			−0.001*** (0.0003)			−0.001** (0.0004)	
FD_2			−0.001** (0.0004)			−0.001** (0.0008)			−0.001** (0.0008)
NORTHERN	0.004 (0.025)	−0.001 (0.022)	0.001 (0.023)	−0.036 (0.041)	−0.043 (0.036)	−0.045 (0.043)	−0.013 (0.040)	−0.020 (0.034)	−0.021 (0.039)
CENTRAL	−0.021 (0.023)	−0.024 (0.021)	−0.022 (0.021)	−0.057 (0.035)	−0.062* (0.032)	−0.062* (0.033)	−0.034 (0.030)	−0.038 (0.031)	−0.038 (0.032)
T2	0.001 (0.024)	0.002 (0.025)	0.003 (0.026)	−0.034 (0.024)	−0.033 (0.023)	−0.033 (0.022)	−0.009 (0.027)	−0.009 (0.031)	−0.008 (0.030)
T3	−0.084*** (0.021)	−0.084*** (0.026)	−0.083*** (0.021)	−0.124*** (0.029)	−0.125*** (0.028)	−0.124*** (0.029)	−0.100*** (0.032)	−0.101*** (0.038)	−0.100** (0.043)
T4	−0.133*** (0.020)	−0.134*** (0.028)	−0.132*** (0.027)	−0.180*** (0.031)	−0.182*** (0.026)	−0.180*** (0.033)	−0.162*** (0.034)	−0.164*** (0.039)	−0.162*** (0.054)
CONST	0.407*** (0.094)	0.401*** (0.105)	0.434*** (0.073)	0.463*** (0.110)	0.465*** (0.108)	0.497*** (0.080)	0.426*** (0.124)	0.421*** (0.132)	0.461*** (0.124)

Table reports coefficients and standard error (in parentheses); ***, **, *: statistically significant al 1%, 5% and 10% respectively.
Columns (1), (2) and (3) are associated with university efficiency scores without the 1st quartile; Columns (4), (5) and (6) are associated with university efficiency scores without the 4th quartile; Columns (7), (8) and (9) are associated with university efficiency scores without the 1st and the 4th quartiles.
All estimates are associated with bootstrapped university efficiency scores in the first stage (Double-boot DEA procedure).

Table 10
SFA directional output distance − Variables affecting inefficiency − Using a Cobb-Douglas production function.

Variables	Model A	Model B	Model C	Model A1	Model B1	Model C1
MED	0.042 (0.034)	0.040 (0.036)	0.038 (0.035)	0.051 (0.033)	0.049 (0.033)	0.054 (0.033)
FPS	−0.0004*** (0.00007)	−0.0003*** (0.00008)	−0.0004*** (0.00007)	−0.0004*** (0.00007)	−0.0004*** (0.00007)	−0.0004*** (0.00007)
MK	−0.381** (0.096)	−0.238** (0.113)	−0.344*** (0.097)	−0.276** (0.137)	−0.318*** (0.121)	−0.316** (0.125)
MK^2	0.758* (0.228)	0.646** (0.260)	0.719*** (0.227)	0.617** (0.275)	0.663** (0.266)	0.669** (0.266)
YEAR_FOND	0.0001*** (0.00006)	0.0001** (0.00007)	0.0001*** (0.00006)	0.0001** (0.00006)	0.0001** (0.00006)	0.0005** (0.00006)
WOMEN	−8.94e-06*** (2.88e-06)	−9.80e-06*** (3.16e-06)	−8.98e-06*** (2.85e-06)	−0.00001*** (3.02e-06)	−0.00001*** (2.86e-06)	−0.00001*** (2.91e-06)
GDP	−8.19e-07 (6.12e-07)			0.00003 (0.00002)		
FD_1		−0.004** (0.001)			−0.0003 (0.0004)	
FD_2			−0.001*** (0.0009)			0.001 (0.001)
NORTHERN	−0.069 (0.050)	−0.075 (0.056)	−0.072 (0.049)	−0.109* (0.060)	−0.117 (0.071)	−0.127 (0.084)
CENTRAL	−0.023*** (0.046)	−0.299*** (0.053)	−0.227*** (0.047)	−0.267*** (0.044)	−0.285*** (0.055)	−0.313*** (0.083)
T2	0.068 (0.098)	0.020 (0.069)	0.070 (0.101)	0.086 (0.101)	0.084 (0.101)	0.073 (0.099)
T3	−0.042 (0.091)	−0.055 (0.070)	−0.041 (0.094)	−0.040 (0.091)	−0.041 (0.092)	−0.046 (0.089)
T4	−0.092 (0.095)	−0.070 (0.072)	−0.093 (0.097)	−0.090*** (0.095)	−0.090 (0.096)	−0.090 (0.094)
CONST	0.195 (0.171)	0.017 (0.166)	0.176 (0.174)	0.270 (0.186)	0.263 (0.192)	0.267 (0.197)

Table reports coefficients and standard error (in parentheses); ***, **, *: statistically significant al 1%, 5% and 10% respectively.
In Models A, B and C, the variables GDP, FD_1 and FD_2 are measured at province level.
In Models A1, B1 and C1, the variables GDP, FD_1 and FD_2 are measured at regional level.

Table 11
SFA directional output distance − Variables affecting inefficiency - Using a Translog production function.

Variables	Model A	Model B	Model C	Model A1	Model B1	Model C1
MED	0.098** (0.048)	0.098** (0.049)	0.104** (0.048)	0.053 (0.046)	0.072 (0.044)	0.063 (0.043)
FPS	−0.0003*** (0.0001)	−0.0003*** (0.0001)	−0.0003*** (0.0001)	−0.0001* (0.0001)	−0.0002* (0.0001)	−0.0001* (0.0001)
MK	−0.349 (0.225)	−0.439** (0.193)	−0.434** (0.199)	−0.518*** (0.134)	−0.350** (0.146)	−0.339** (0.144)
MK^2	0.627 (0.456)	0.758* (0.430)	0.762* (0.429)	0.948*** (0.308)	0.814** (0.330)	0.777** (0.325)
YEAR_FOND	0.0001* (0.0001)	0.0002* (0.0001)	0.0001* (0.0001)	0.0002*** (0.0001)	0.0002** (0.0001)	0.0002*** (0.00009)
WOMEN	−0.00003*** (0.000005)	−0.00002*** (0.000005)	−0.00003*** (0.000005)	−0.00003*** (0.000006)	−0.00003*** (0.000006)	−0.00003*** (0.000006)
GDP	0.00004 (0.00005)			−0.000006*** (0.000002)		
FD_1		0.0004 (0.0008)			−0.006*** (0.001)	
FD_2			0.001 (0.002)			−0.0110*** (0.002)
NORTHERN	−0.303*** (0.108)	−0.292** (0.127)	−0.290** (0.126)	−0.256*** (0.070)	−0.279*** (0.071)	−0.301*** (0.071)
CENTRAL	−0.368*** (0.073)	−0.383*** (0.093)	−0.407*** (0.129)	−0.370*** (0.061)	−0.377*** (0.062)	−0.399*** (0.060)
T2	−0.115* (0.065)	−0.120* (0.065)	−0.128* (0.065)	−0.135** (0.058)	−0.143** (0.058)	−0.138** (0.057)
T3	−0.249*** (0.079)	−0.253*** (0.079)	−0.262*** (0.080)	−0.254*** (0.067)	−0.278*** (0.068)	−0.261*** (0.066)
T4	−0.292*** (0.080)	−0.297*** (0.080)	−0.304*** (0.081)	−0.286*** (0.071)	−0.307*** (0.071)	−0.288*** (0.069)
CONST	0.410 (0.265)	0.374 (0.268)	0.395 (0.288)	0.427* (0.231)	0.457** (0.229)	0.520** (0.228)

Table reports coefficients and standard error (in parentheses); ***, **, *: statistically significant al 1%, 5% and 10% respectively.
In Models A, B and C, the variables GDP, FD_1 and FD_2 are measured at province level.
In Models A1, B1 and C1, the variables GDP, FD_1 and FD_2 are measured at regional level.

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