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# Explaining (in)efficiency in higher education: a comparison of parametric and non-parametric analyses to rank universities

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## Abstract

In recent years more and more numerous are the rankings published in the 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. The aim of this study is to rank higher education institutions (HEIs) in Italy, comparing parametric and non-parametric approaches: we firstly apply a so-called double bootstrap Data Envelopment Analysis (DEA) to generate unbiased coefficients (Simar and Wilson, 2007) and then a Stochastic Frontier Analysis (SFA), modelling the production set through an output distance function, applying a within transformation to data as developed by Wang and Ho (2010), to evaluate which determinants have an impact on universities' efficiencies. The findings reveal that, on average and among the macro-areas of the country, the level of efficiency does not change significantly among estimation methods which, instead, generate different rankings. This may guide universities' managers and policymakers 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. Variables describing institution, market place and environment have an important role in explaining (in)efficiency.

**Keywords**: Universities, Efficiency, Data Envelopment Analysis, Stochastic Frontier Analysis

**JEL Codes**: I21, I23, C14, C67

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## 1. Introduction

The public budget constraints, due to recent economic crises and the new funding mechanism of the Italian university system (see Donina et al. 2015 for a description of university governance in Italy), have brought back to the center of both academic and political debates the assessment of universities' performances. In recent years, more and more numerous are the rankings published in the newspapers or technical reports available, covering many aspects of higher education, but in many cases with very conflicting results between them (see De Witte and Hudrlikova, 2013 for a detailed discussion on university rankings and for an alternative methodology to rank universities). Indeed, departments' or universities' efficiencies depend on the set of variables considered and on the methods of analysis employed. One of the main problems is, in fact, which variables effectively investigate in order to evaluate the tertiary education system. It is commonly acknowledged that universities have primarily a double mission: teaching and research[1]; even though, from the perspective of students, the higher education institutions (HEIs) primary clients, teaching is often considered the main goal, in today's rapidly-changing political and economic climate, both goals have become increasingly important. Regarding the former contribution (i.e. teaching), HEIs might contribute to increase the level of human capital (Etzkowitz, 2003); highly skilled and well-educated individuals are one of the main outputs of universities and at the same time are considered as the ultimate drive of economic development (Florida et al. 2008). Improvements in the population's human capital lead to improvements in labour, which in turn lead to higher activity rates and lower unemployment rates, thus fostering greater long-term economic growth in the region. Human capital creation is, indeed, one of the long-term, knowledge-based supply-side effects according to Florax (1992) and the production of highly educated graduates is likely to cause positive supply-side effects in the regional economy (Shubert and Kroll, 2014). With regard to the latter task (i.e. research), academic research quality is universally recognised as influencing market-related university–firm interactions, mainly through contract and collaborative research (D'Este and Iammarino, 2010; Laursen *et al.* 2011) and licensing (Mowery and Ziedonis, 2015). Universities' research activities contribute to the creation of knowledge spillovers leading to an improvement of the economies (Goldstein and Renault, 2004) and have also impact on the distribution of innovation (Del Barrio-Castro and García-Quevedo, 2005). In recent years, 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" (OECD 2008). Both quantitative and qualitative indicators were developed to accurately evaluate the management of public universities, their productivity in research and teaching and the overall success of their administration; as a consequence, (public) funds to higher education institutions are now related to performance indicators according to which evaluate their management and productivity. See Dyson (2000), for a discussion on the need for performance measurement and strategy.

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 (SFA), and non-parametric, such as Data Development Analysis (DEA). However, there is no general consensus about which one has to be adopted to measure

[1]There is also a third function of the universities which is known as the knowledge transfer to industry and links of higher education institutions with industrial and business surroundings. Unfortunately, due to the unavailability of data, we are not able to take into account this aspect in our analysis.

higher education institutions efficiency, as these two main approaches have not only different features, but also advantages and disadvantages (Lewin and Lovell 1990)[2]. DEA does not require, ex-ante, an assumption regarding the functional form of the cost or production function (contrary to SFA) and allows to manage multiple inputs and outputs jointly. Nevertheless, this method has its drawbacks. Firstly, DEA does not account for stochastic noise in the data. For instance, the results may be severely biased when measurement errors are present. Secondly, in two stage approaches, the results may be biased due to the presence of serial correlation (Simar and Wilson, 2007). To obtain unbiased coefficients, a DEA two-stage with a bootstrap procedure introduced by Simar and Wilson (2007) could be applied 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, a so-called double-bootstrap method could be also used 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, see Wolszczak-Derlacz and Parteka (2011), who examined the efficiency of HEIs in selected European countries, and Curi et al. (2013) who, instead, analysed the efficiency of the technology transfer operated by the French university system (see also Haelermans and Ruggiero 2013; Coco and Lagravinese, 2014; Brennan et al. 2014) for an application regarding secondary education). On the other hand SFA requires an assumption regarding the functional form of the cost or production function. The selection of a function is not a clear-cut task in higher education as Kraus (2004) pointed out. The most recent literature (Greene, 2005; Wang & Ho, 2010) 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 (2010), in order to incorporate heterogeneity in panel data in the stochastic frontier model, show that first-difference and within transformation can be analytically performed on this model 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 Greene, 2005). However, to the best of our knowledge, this procedure has not been frequently used in the higher education environment, yet. 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 (Lovell et al., 1994; Coelli and Perelman, 2000). This technique is particularly useful when no price information, regarding inputs and outputs, is available (Coelli, 2000). Abbott and Doucouliagos (2003) estimated output distance functions in order to examine the relationship between competition and efficiency in Australian and New Zealand universities. Output distance functions have also be estimated by Johnes (2014), who analysed the effect of efficiency on merger activities in the English higher education sector. So far, to the best of our knowledge, no papers have investigated the efficiency of Italian HEI combining both non-parametric (DEA) and parametric

[2]On one hand, the non-parametric method does not require the building of a theoretical production frontier, but the imposition of certain, a priori, hypotheses about the technology (free-disposability, convexity, constant or variable returns to scale). However, if these assumptions are too weak, the level of inefficiency could be systematically underestimated in small samples, generating inconsistent estimates. Furthermore, this method is very sensitive to the presence of outliers. On the other hand, the parametric method uses a theoretical analysis to construct the efficient frontier, it's not sensitive to extreme values because imposes some assumptions on the error distribution, but must deal with the problem of decomposing the error term. In particular, SFA, proposed by Aigner et al. (1977), Meeusen and Van den Broeck (1977) and Battese and Corra (1977), assumes that the error term is composed by two components with different distributions (see Kumbhakar and Lovell (2000) for analytical details on stochastic frontier analysis). The first component, regarding the "inefficiency", is asymmetrically distributed (typically as a semi-normal), while the second component, concerning the "error", is distributed as a white noise. In this way, it is necessary to assume that both components are uncorrelated (independent) to avoid distortions in the estimates. Instead, DEA, unlike SFA, assumes that the "error" is fixed over time, while the "inefficiency" component is normally distributed.

approaches (SFA). Therefore, in order to make the estimates more robust and comprehensive, we firstly apply both a double-bootstrap procedure and a two-stage bootstrap Data Envelopment Analysis (DEA), to generate unbiased coefficients (Simar and Wilson, 2007), and then we employ a Stochastic Frontier Analysis (SFA), modelling the production set through an output distance function, using a within transformation to data as developed by Wang and Ho (2010).The first objective of the paper, is to study the efficiency of Italian HEIs[3] using data over the four-years from 2008 to 2011, relying on different criteria of performance indicators, in order to take into account the multiple objectives of higher education institutions, such as both teaching and research related outcomes. The second contribution of this work, beyond the analyses on HEIs' performances already performed in the literature, is bringing new evidence on the importance of comparing the efficiency estimates derived from various estimation methods (i.e. both parametric and non-parametric techniques) and using the results from these evaluation processes to rank universities and to provide guidance to university managers and policy makers. 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 techniques for estimating what determines the efficiency, the Tobit-estimator has mainly been applied. However, Simar and Wilson (2007) have emphasized two possible problems stemming from applying Tobit in this context. Firstly, the results may be biased in the presence of serial correlation between variables at the two stages; secondly, the efficiency scores may be biased in finite samples. In order to obtain unbiased beta coefficients with valid confidence intervals, Simar and Wilson (2007) proposed a double bootstrap procedure 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 analyze the technical efficiency[4] using a double-bootstrap DEA method (Simar and Wilson, 2007). In particular, we focus on an output-oriented model, following Agasisti and Dal Bianco (2009), 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 education according to the fact that the resources used can be considered fixed and that universities cannot

[3]See Agasisti (2009), Potì and Reale (2005), Bini and Chiandotto (2003) and Buzzigoli et al. (2010) for a brief review of the university system in Italy.

[4]The technical efficiency refers to the capacity of the Decision Making Unit (DMU), given the technology used, to produce the highest level of output from a given combination of inputs, or alternatively, to use the least possible amount of inputs for a given output. Specifically, given that the focus is on the higher education system, technical efficiency means, according to Abbott and Doucouliagos (2003), that "the technically efficient university is not able to deliver more teaching plus research output (without reducing quality) given its existing labor, capital and other inputs".

influence, at least in the short run, the human, financial and physical capital available (Bonaccorsi et al. 2006). 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:

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

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 inputsx remain constant.
We assume variable return to scale (VRS); the DEA-VRS is probably the most reliable in our case as suggested by Agasisti (2011), 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:

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

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 ($z_i$):

$$\widehat{\delta_\iota} = z_j \beta + \varepsilon_j \qquad j = 1, \dots, n \tag{4}$$

where $\varepsilon_j$ 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 a unknown way; moreover, the disturbance error $\varepsilon_j$ 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 (2008) which is freely available online, and the truncated regression models were then performed in STATA 12 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 (1995), 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 (Lovell *et al.* 1994; Coelli and Perelman, 2000). Moreover, this technique is particularly useful when no price information regarding inputs and outputs is available (Coelli, 2000). Specifically, and following Abbott and Doucouliagos (2003) and Johnes (2014), 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 (Greene, 2005; Wang and Ho, 2010). For instance, students' or researchers' (average) innate abilities may be an important determinant of their individual academic achievements and thus account for an important share of the heterogeneity in data when evaluating the efficiency of the institution in which they are studying or working. As Wang and Ho (2010) 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 within transformation to data as developed by Wang and Ho (2010). By this transformation, the sample mean of each panel is subtracted from every observation in the panel, removing time-invariant individual effects from the model. Following the notation in Wang and Ho (2010), the transformation employed to our model is:

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

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

$$\widetilde{w}_{i.} = (w_{i1.}, w_{i2.}, \dots, w_{iT.})' \quad (6)$$

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

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

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:

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

By a within transformation, $\alpha_i$ (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[5] by $\tilde{y}_i$, that guarantees the linear homogeneity of degree 1 in outputs ($\sum_{m=1}^{M} \tilde{\alpha}_m = 1$) as suggested by Lovell et al. (1994), the output oriented distance function becomes:

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

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 $ln(\widetilde{D}_{i.}^{o})$ is not observable. Then, in order to solve this problem, we can re-written $ln(\widetilde{D}_{i.}^{o}/\tilde{y}_{i.}) = ln(\widetilde{D}_{i.}^{o})$ - $ln(\tilde{y}_{i}.)$. Thus, we transfer $ln(\widetilde{D}_{i.}^{o})$ to the residuals, i.e. on the right and side of the equation (9), and using $-ln(\tilde{y}_{i.})$ as dependent variable (Coelli and Perelman, 2000). In our case, we follow Paul et al. (2000), i.e. imposing $ln(\tilde{y}_i)$. The equation (9) thus becomes:

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

where $\tilde{u}$ *t*erms stands for inefficiency component, obtained from the truncation to zero of the distribution $N(\tilde{m}_i, \tilde{\sigma}_u^2)$, 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.$N(0, \tilde{\sigma}_v^2)$ 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 (2002) and Alvarez et al. (2006)) because produces estimation problems in our model. In fact, as suggested in literature (see for instance Wang and Ho, 2010), 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.

[5]Since they are mathematically equivalent, the choice of the normalizing variable is innocuous (see Restrepo-Tobon and Kumbhaka, 2013, p. 16). Then, we normalize by grants for research (see Section 3 for more details on the output used in the analysis).

Specifically, a Cobb-Douglas[6] production function[7] is preferred in this paper firstly because it allows us to overcome the multicollinearity problem and biases in the coefficients associated to estimate a few number of parameters with respect to the translog function and secondly because it's more comparable with a non-parametric approach.

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 National Committee for the Evaluation of the University System (CNVSU) website[8]. We exclude all private sector universities, due to the absence of comparable data on academic research variables; this leaves us with a sample of 53 universities[9], each of which yields data over the four year period, so we have a total of 212 observations.

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. More specifically, the first input is the number of academic staff ($ACAD_{STAFF}$). 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 Johnes, 2014; Agasisti and Dal Bianco, 2009)[10]. 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

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[6]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. This paper uses a Cobb-Douglas function. However, there is no general consensus about which one is to be adopted in the higher education environment (for a discussion on the different function forms, see Agasisti and Johnes, 2009). 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 us to overcome 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 function (see Laureti, 2008, who uses a Cobb-Douglas function in order to model exogenous variables in human capital formation).

[7]Therefore, all inputs and outputs are in log level.

[8] Specifically, data have been collected by the Italian Ministry of Education, Universities and Research Statistical Office.

[9]Which is very representative of the higher education system in Italy, corresponding to almost 90% of the total number of public universities in the country (we are not able to cover the complete population of universities due to missing information on some of the variables used in the analysis).

[10] The variable $ACAD_{STAFF}$ indicates the number of total academic staff adjusting for the respective academic position. Specifically, the academic staff has been disentangled in four categories, namely professors, associate professors, assistant professors and lectures. In order to take into account this categorization, 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 Madden et al. 1997) and assuming that a professor is expected to produce more research and teaching work than an associate professors and so on (see Carrington et al. 2005). We follow Halkos et al. (2012) where professors are assigned with 1, associate professors with 0.75, assistant professors with 0.5 and lecturers with 0.25. They basically choose weights so that the distance between two ranks is 1/4=0.25. Thus, we use the following aggregate measure of human capital input: Academic Staff ($ACAD_{STAFF}$)=1*professors+0.75*associate professors+0.50* assistant professors +0.25* lectures. Unfortunately, we do not have information on the auxiliary staff such as the administrative staff.

lyceum[11]($ENR_{LYC}$), 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 (Boero *et al.* 2001; Smith and Naylor 2001; Arulampalam *et al.* 2004; Lassibille 2011). The underlying theory is that ability of students lowers their educational costs and increases their motivation (DesJardins *et al.* 2002). 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)[12]. The fourth and last input is the total number of students (STUD) in order to measure the quantity of undergraduates in each university[13] (Agasisti and Dal Bianco, 2009).

Moving to the output side, two measures of outputs are included in the model reflecting the teaching and research functions of HEIs: 1 – number of graduates weighted by their degree classification; 2 – research grants. According to Catalano et al. (1993) "the task assigned to universities is to produce graduates with the utilization and the combination of different resources" and Madden et al. (1997) used the number of graduates under the hypothesis that the higher is the number of graduates the higher is the quality of teaching[14]. Also Worthington and Lee (2008) considered the number of undergraduate degrees awarded an obvious measure of output for any university. Thus, the first output considered in the analysis is the number of graduates weighted by their degree classification[15] ($GRAD_{MARKS}$), in order to capture both the quantity and the quality of teaching (see also Johnes, 1996; Johnes 2006; Madden *et al.* 1997). 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 (De Groot *et al.* 1991) and weighted indexes of publications (Athanassoupoulos and Shale, 1997; Johnes and Johnes, 1993; Tyagi *et al.* 2009; Johnes and Yu, 2008; Halkos *et al.* 2012). Information on the number of publications is not

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[11] 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. This secondary school is divided in two types: a) vocational schools are higher-level learning institutions which are specialized in providing students with the vocational education and technical skills they need in order to perform the tasks of a particular job; b) non-vocational secondary schools, instead, are more academic oriented and are specialized in providing the students the skills needed in order to enroll in the university. The latter, in Italy, is also called Lyceum. So, basically, the variable percentage of enrolments who attended a lyceum ($ENR_{LYC}$) is the percentage of students who attend a Lyceum (i.e. secondary schools who prepare students to the university). In other words, supported by the literature on the education system using Italian data, the idea is that the higher is the percentage of enrolments who come from "Lyceum" the higher is the quality of the university.

[12] 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.

[13] The second and third inputs ($ENR_{HSG}$ and $ENR_{LYC}$) are used as percentages in order to avoid a double counting problem due to presence of the total number of students (STUD) among the inputs. In this way we are able to measure the quantity of undergraduates in each university (through STUD) and include in the production process also two important information regarding the quality of the students enrolled in each university ($ENR_{HSG}$ and $ENR_{LYC}$).

[14] The liability of this measure is still not clear in the literature. See Kao and Hung (2008) and Abbott and Doucouliagos (2003) for a discussion.

[15] For the readers who are not familiar with the characteristics of the Italian higher education system, in Italy students can graduate obtaining marks from 66 to 110 with distinction. This grade is calculated mainly according to the average grades students have obtained in the exams; then a certain number of points is added after the final dissertation has been graded. 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 as follows: $GRAD_{MARKS}$=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+0.50*graduates with marks between 66 and 90. We've also used just the number of graduates without weighting by their degree classification. In all cases results are similar.

available to us, thus we use research grants (RES) as a second output and as a proxy of research outputs (see Abbott and Doucouliagos, 2003; Agasisti and Johnes, 2010; Kao and Hung, 2008; Agasisti and Johnes, 2009; Agasisti *et al.* 2012; Worthington and Lee, 2008). According to Agasisti and Johnes (2010), "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 (Cave *et al.*, 1991; Tomkins and Green, 1988). Specifically, in our case, it represents the amount that the government is willing to pay the universities for the research they produce. 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 (2008) this is more important when using citation counts or number of patents than research income measure. Moreover, according to Johnes (2014), 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". Thus, also considering that there are no clear criteria for deciding on the appropriate length of lag (Emrouznejad and Thanassoulis, 2005[16]) and following Johnes (2014), we use a static model in our analysis. See also Frey and Rost (2010) for a discussion on the appropriate measures of research quality and quantity.

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.

[Table 1] around here

*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:

$$\delta_{i,j,t} = \alpha + \beta_1 MED_{i,j,t} + \beta_2 FPS_{i,j,t} + \beta_3 MK_{i,j,t} + \beta_4 MK_{i,t}^2 + \beta_5 YEAR\_FOND_{i,j,t} + \beta_6 WOMEN_{i,j,t} + \beta_7 AV_{j,t} + \beta_8 FD_{j,t} + TIME + u_{i,j,t} \quad (11)$$

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

[16] One study, which develops a dynamic DEA model to capture the inter-temporal aspect, compares the results of the dynamic model with those derived from a static (or conventional) DEA model in the context of higher education, and finds considerable overall agreement between the efficiencies produced from the two approaches (Emrouznejad and Thanassoulis, 2005).

specificity of faculty composition (see Kempkes and Pohl, 2010, 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 pays by the students over the total number of students, in order to take into account the services offered by the institution[17]; $MK$ 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; $YEAR\_FOND$ is the year of foundation of the university as a proxy for the level of tradition of a given HEIs as 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; $AV$ is the added value per capita corresponding to the difference between the production value of goods and services created by individual productive branches and the value of the intermediate goods and services consumed by them, with the aim of controlling for the growth of the economic system in terms of new goods and services made available to the community for final use[18]; $FD$ represents the financial development measured as aggregate private credits relative to GDP (as robustness we also use aggregate private deposits relative to GDP). Finally, $TIME$ denotes dummies trend capturing the presence of exogenous effects on the phenomenon analysed, while $u$ is the vector of error terms. We measure $MED, FPS, YEAR\_FOND$ and $WOMEN$ at university level, while $MK$ and $FD$ are instead measured at regional level. See Table 2 below, for more details on the specification of inputs, outputs and exogenous factors.

[Table 2] around here

## *4. Results*

### *4.1. Efficiency scores*

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

[17]More specifically, it corresponds to the fees income received from undergraduates students. For the readers who are not familiar with the Italian higher education system, Italian universities are free to set their own student fees, even though their amount is partially constrained by a national regulation and there is a legal minimum fee for enrolment and maximum level for student contributions to costs and services, which cannot exceed 20% of state funding. Usually, the level of these fees is quite low (around 1,200€ per year) and covers only a small fraction of the real cost per student; nevertheless, this source of income gained importance in the last years (to contrast the reduction of public funds) and now represents, on average, 15% of the total university budget. Fees do not depend on the subject studied and are usually set according to the ISEE index which is an instrument used to measure the actual property and income position of citizens that apply for social services under favourable terms and is determined by combining and evaluating three elements: income, assets and composition of the household. To calculate the ISEE index to the fiscal year at time t, gross income to all members of the household at time t as reported at time t+1 is used, along with the composition of the self-reported information about the value of household's assets in real estate at the end of t year, cadastral certificates or other documents regarding real property, etc. Therefore, fees are paid by students proportionally to the amount declared in the ISEE. Therefore, in some cases, students are exempted from paying tuition fees depending on their financial situation and also on their academic performances. It has also to be said that however, student fees represent just a part of universities' income. For the remaining part, universities are mostly funded directly by the Ministry of Education, which also has the major responsibility for regulating higher education (for example, staff salaries, rules to activate courses).

[18]This measure can be intended as an alternative, more robust indicator for GDP per capita, measured at regional level.

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).

[Table 3] around here

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., Agasisti and Dal Bianco, 2009). 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. Table 4 below, instead, presents the estimated parameters of the stochastic education distance frontier presented in Section 2.2.; 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[19]. 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 4] around here

Table 5, 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 created by Simar and Wilson, 2007), 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,

[19]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.

Napoli L'Orientale and Napoli Parthenope are located), shows lower performances with an average of 0.6465 among all the years.

[Table 5] around here

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 5). When we consider the big city areas where many universities are located, the Rome area (where Roma La Sapienza, Roma Tor Vergata and Roma Tre are located), is particularly efficient with an average efficiency of 0.8728 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 0.8713 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 0.6418 among all the years.

The main difference, among the two estimation methods employed in the paper, regards the university rankings (seeTable 6, 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), 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 university (Università degli Studi di Torino) assumes the same position ($6^{th}$). While, all the other universities which are present in both rankings, are positioned differently.

[Table 6] around here

Boxplots and Kernel distributions of efficiency scores (pooling all years) are presented in Figure 1 below. Differences between 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.

[Figure 1] around here

*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 (see Tables 7 and 8 below) and SFA (see Table 9 below) 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 a negative sign of estimated parameter indicates lower inefficiency (greater efficiency).

[Table 7] around here

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. (2012), 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 (2002), Anderson et al. (2007) and Chapple et al. (2005) 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[20]. 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 positive association between efficiency and fees of Italian universities is in Agasisti and Wolszczak-Derlacz (2014)[21]. 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 (specifically when bootstrapped efficiency scores are estimated, see Column 1, 2 and 3, Table 7). 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. 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. 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 (specifically when not-bootstrapped efficiency scores are estimated, see Column 4, 5 and 6, Table 7). A negative and statistically significant coefficient has been found on the variable value-added (AV), 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. The importance of using a double bootstrapped approach is evident not only when looking at the universities' efficiency scores (see Table 5 above), but also when the (in)efficiency score determinants are taken into account (see Table 7, Columns 1, 2 and 3 vs Column 4, 5 and 6). See for instance the reduction in the magnitude of the coefficient related to the presence of a Medical school (MED) and the measure of the market share (MK) which become statistically significant when the bootstrap is performed.

[20] For a different perspective, see Siegel et al. (2008) who, instead, show that the presence of a medical school does have a positive and statistically significant impact on universities' efficiencies.
[21] They underline that this result could depend on the fact that those universities "are more responsive towards students' needs and use the money in a more efficient way (for instance, on teaching services that are able to help "producing" more graduates)".

[Table 8] around here

Regarding the two stage DEA approach, for robustness, we also further investigate whether the distribution of the efficiency affect the estimates, in the second step. Indeed, we divide universities in quartiles, and repeat the analysis firstly removing from the sample those universities with an efficiency score in the first quartile - taking out the less efficient universities – (see Table 8, Columns 1, 2, 3), then those with efficiencies scores in the last quartiles - taking out the more efficient universities – (see Table 8, Columns 4, 6, 7) and ultimately taking out both (see Table 8, Columns 7, 8, 9). Results are confirmed. Finally, Table 9 shows the determinants of inefficiency scores when the SFA approach has been used. When comparing non-parametric and parametric methods, (see Tables 7 and 9), results do not show important differences, apart from the presence of a Medical school (MED), which is still positive (meaning a lower efficiency for universities with medical school) but it is not statistically significant anymore.

[Table 9] around here

## 5. *Conclusions*

The main aims of this research were to evaluate the efficiency of Italian universities, and to investigate some exogenous characteristics affecting their efficiency, underlining the importance of comparing the efficiency estimates derived from various estimation methods, in order to rank universities. In order to reach these goals, both parametric and non-parametric techniques have been applied; we firstly apply both a double-bootstrap procedure and a two-stage bootstrap Data Envelopment Analysis (DEA), to generate unbiased coefficients (Simar and Wilson, 2007) and then a Stochastic Frontier Analysis (SFA), modelling the production set through an output distance function, applying a within transformation to data as developed by Wang and Ho (2010), to evaluate which determinants have an impact on universities' efficiencies.

Results reveal, as customary for the literature on Italian universities, 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. 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 over-estimated suggesting the importance of using a bootstrapped DEA approach. On average, the level of efficiency does not change very much among estimation methods even though the universities are ranked differently. For instance, looking at the universities ranked in the first 10 position, 8 of them are present only in one of the rankings; instead, only few of them are present in both. Moreover, among them, only one of the university assumes the same position, while all the other universities which are present in both rankings, are positioned differently. In other words, the methods of analysis employed do matter when ranking universities.

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; indeed, 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. The higher is the level of fees per capita the lower is the universities' inefficiency as well as that the higher is the value added per capita the lower is the technical level of inefficiency. The findings 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.

This exercise provide guidance to university managers and policymakers, warning them that the estimates of the level of efficiency could vary by estimation methods and, more importantly, that the ranking of universities may change; this is particularly important considering that rankings have a strong impact on academic decision-making and behaviour, and on the structure of the institutions (Hazelkorn, 2007), that higher education institutions are focusing on the criteria with the highest impact on the ranking (Tofallis 2012), and that also students and graduates recruiters follow the hierarchy of institutions (see Clarke, 2007; Harvey, 2008). In other words, as both human and financial resources might depend on how the university are positioned in such rankings, it is useful to providing further light on the delicate processes of evaluating the efficiency of HEIs.

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## TABLES AND FIGURES

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

| | | Mean values | | | |
|---|---|---|---|---|---|
| | | *North-Western* | *North-Eastern* | *Central* | *Southern* |
| *Inputs* | | | | | |
| $ACAD_{STAFF}$[1] | *# of academic staff (university level)* | 1043.56 (648.21) | 1061.50 (832.26) | 1221.82 (893.12) | 797.75 (641.73) |
| $ENR_{HSG}$[2] | *% 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) |
| $ENR_{LYC}$[2] | *% 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) |
| *AV* | *Value added (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*
*[1]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). [2]Both $ENR_{HSG}$ and $ENR_{LYC}$ are percentages of the total number of students enrolled.*

*Table n. 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; AV; 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*
*AV: Value added*
*FD_1: Financial Development (aggregate private credits / GDP)*
*FD_2: Financial Development (aggregate private deposits / GDP)*

*Table n. 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) |
| Geographical areas | No boot | Boot | Bias | No boot | Boot | Bias | No boot | Boot | Bias | No boot | Boot | Bias | No boot | Boot | Bias |
| 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.*

*Table n. 4–SFA directional output distance efficiency scores over the period 2008-2011 by geographical areas*

| | Model A | | | | | Model B | | | | | Model C | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Geographical areas | 2008 | 2009 | 2010 | 2011 | Tot | 2008 | 2009 | 2010 | 2011 | Tot | 2008 | 2009 | 2010 | 2011 | Tot |
| 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 AV 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 n. 5 - DEA technical efficiency and SFA directional output distance efficiency scores over the period 2008 2011 by university*

| | | DEA efficiency scores | | | SFA efficiency scores | | |
|---|---|---|---|---|---|---|---|
| | | (No boot) | (Boot) | (Bias) | (A) | (B) | (C) |
| 1 | Università Politecnica delle Marche- Ancona | 0.8135 | 0.7548 | 0.0587 | 0.6771 | 0.8014 | 0.6605 |
| 2 | Università della Calabria - Arcavacata di Rende | 0.6642 | 0.6068 | 0.0574 | 0.5872 | 0.6670 | 0.5714 |
| 3 | Politecnico di Bari | 0.6348 | 0.5654 | 0.0694 | 0.4452 | 0.5280 | 0.4395 |
| 4 | Università degli Studi di Bari | 0.8164 | 0.7408 | 0.0756 | 0.7459 | 0.8421 | 0.7342 |
| 5 | Università degli Studi del Sannio - Benevento | 0.6157 | 0.4544 | 0.1613 | 0.4224 | 0.5072 | 0.4139 |
| 6 | Università degli Studi di Bergamo | 1.0000 | 0.7161 | 0.2839 | 0.6033 | 0.7030 | 0.5898 |
| 7 | Università degli Studi di Bologna | 1.0000 | 0.8306 | 0.1694 | 0.9735 | 0.9880 | 0.9718 |
| 8 | Università degli Studi di Brescia | 0.5669 | 0.5226 | 0.0443 | 0.5742 | 0.6741 | 0.5649 |
| 9 | Università degli Studi di Cagliari | 0.7890 | 0.7088 | 0.0802 | 0.6890 | 0.7801 | 0.6825 |
| 10 | Università degli Studi del Molise - Campobasso | 0.8725 | 0.7076 | 0.1649 | 0.5063 | 0.5768 | 0.4998 |
| 11 | Università degli Studi di Cassino | 0.7834 | 0.6092 | 0.1742 | 0.5378 | 0.6680 | 0.5226 |
| 12 | Università degli studi di Catania | 0.7980 | 0.7080 | 0.0900 | 0.7461 | 0.8467 | 0.7325 |
| 13 | Università degli Studi "Magna Grecia" - Catanzaro | 0.8080 | 0.6973 | 0.1107 | 0.4988 | 0.5612 | 0.4897 |
| 14 | Università degli Studi Gabriele D'Annunzio - Chieti e Pescara | 0.9097 | 0.7727 | 0.1370 | 0.6729 | 0.7574 | 0.6670 |
| 15 | Università degli Studi di Ferrara | 0.6677 | 0.6149 | 0.0528 | 0.6623 | 0.7534 | 0.6531 |
| 16 | Università degli Studi di Firenze | 1.0000 | 0.7585 | 0.2415 | 0.9577 | 0.9876 | 0.9527 |
| 17 | Università degli Studi di Foggia | 0.6259 | 0.5760 | 0.0499 | 0.4862 | 0.5361 | 0.4797 |
| 18 | Università degli Studi di Genova | 0.9286 | 0.8375 | 0.0911 | 0.8480 | 0.9453 | 0.8519 |
| 19 | Università del Salento - Lecce | 0.8436 | 0.7703 | 0.0733 | 0.6417 | 0.6777 | 0.6313 |
| 20 | Università degli Studi di Messina | 0.6694 | 0.6137 | 0.0557 | 0.6576 | 0.7336 | 0.6459 |
| 21 | Politecnico di Milano | 0.9544 | 0.8850 | 0.0694 | 0.9172 | 0.9905 | 0.9134 |
| 22 | Università degli Studi di Milano | 0.9575 | 0.8129 | 0.1446 | 0.9408 | 0.9921 | 0.9363 |
| 23 | Università degli Studi - Milano-Bicocca | 0.8112 | 0.7291 | 0.0821 | 0.7559 | 0.9845 | 0.7503 |
| 24 | Università degli Studi di Modena e Reggio Emilia | 0.6802 | 0.6164 | 0.0638 | 0.7053 | 0.8300 | 0.6941 |
| 25 | Seconda Università degli studi di Napoli | 0.6210 | 0.5707 | 0.0503 | 0.6090 | 0.7286 | 0.6066 |
| 26 | Università degli Studi "Federico II" - Napoli | 0.8058 | 0.7035 | 0.1023 | 0.8700 | 0.9657 | 0.8636 |
| 27 | Università degli Studi "L' Orientale" - Napoli | 0.9837 | 0.7639 | 0.2198 | 0.6292 | 0.7271 | 0.6251 |
| 28 | Università degli Studi "Parthenope" - Napoli | 0.6246 | 0.5479 | 0.0767 | 0.4593 | 0.5877 | 0.4553 |
| 29 | Università degli Studi di Padova | 0.9380 | 0.8504 | 0.0876 | 0.9481 | 0.9788 | 0.9413 |
| 30 | Università degli Studi - Palermo | 0.8431 | 0.7391 | 0.1040 | 0.7584 | 0.8363 | 0.7480 |
| 31 | Università degli Studi di Parma | 0.7091 | 0.6557 | 0.0534 | 0.7563 | 0.8733 | 0.7454 |
| 32 | Università degli Studi di Pavia | 0.8219 | 0.7440 | 0.0779 | 0.7882 | 0.8646 | 0.7787 |
| 33 | Università degli Studi di Perugia | 0.7972 | 0.7358 | 0.0614 | 0.8151 | 0.9376 | 0.8030 |
| 34 | Università degli Studi di Pisa | 0.8051 | 0.7219 | 0.0832 | 0.8841 | 0.9677 | 0.8651 |
| 35 | Università degli Studi della Basilicata - Potenza | 0.9119 | 0.6522 | 0.2597 | 0.4512 | 0.5213 | 0.4409 |
| 36 | Università degli Studi Mediterranea - Reggio Calabria | 0.5158 | 0.4451 | 0.0707 | 0.4558 | 0.5421 | 0.4453 |
| 37 | Università degli Studi di Roma Tre | 0.8849 | 0.8092 | 0.0757 | 0.8317 | 0.9846 | 0.8329 |
| 38 | Università degli Studi "La Sapienza" - Roma | 1.0000 | 0.6854 | 0.3146 | 0.9827 | 0.9942 | 0.9829 |
| 39 | Università degli Studi di "Tor Vergata" - Roma | 0.7936 | 0.7367 | 0.0569 | 0.8041 | 0.9814 | 0.8100 |
| 40 | Università degli Studi di Salerno | 0.5799 | 0.5302 | 0.0497 | 0.5586 | 0.6503 | 0.5489 |
| 41 | Università degli Studi di Sassari | 0.6374 | 0.5757 | 0.0617 | 0.5819 | 0.6623 | 0.5734 |
| 42 | Università degli Studi di Siena | 1.0000 | 0.8128 | 0.1872 | 0.9430 | 0.9738 | 0.9380 |
| 43 | Università degli Studi di Teramo | 1.0000 | 0.6816 | 0.3184 | 0.4638 | 0.5430 | 0.4552 |
| 44 | Politecnico di Torino | 0.8202 | 0.7294 | 0.0908 | 0.7161 | 0.8562 | 0.7104 |
| 45 | Università degli Studi di Torino | 0.9000 | 0.7823 | 0.1177 | 0.9377 | 0.9809 | 0.9337 |
| 46 | Università degli Studi - Trieste | 0.8302 | 0.7483 | 0.0819 | 0.7739 | 0.8364 | 0.7697 |
| 47 | Università degli Studi - Udine | 0.6904 | 0.6242 | 0.0662 | 0.7134 | 0.8669 | 0.7066 |
| 48 | Università dell' Insubria - Varese | 0.6787 | 0.5866 | 0.0921 | 0.6200 | 0.7247 | 0.6090 |
| 49 | Venezia - Università IUAV | 1.0000 | 0.6733 | 0.3267 | 0.8148 | 0.8878 | 0.8039 |
| 50 | Università degli Studi "Cà Foscari" - Venezia | 0.9321 | 0.8446 | 0.0875 | 0.8106 | 0.8906 | 0.7975 |
| 51 | Università degli Studi del Piemonte orientale "A. Avogadro" | 0.6026 | 0.5250 | 0.0776 | 0.5601 | 0.6252 | 0.5538 |
| 52 | Università degli Studi di Verona | 0.7625 | 0.6946 | 0.0679 | 0.7268 | 0.8513 | 0.7162 |
| 53 | Università della Tuscia - Viterbo | 1.0000 | 0.6974 | 0.3026 | 0.7101 | 0.7988 | 0.6941 |

*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 AV 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, ME, FPS, MK, YEAR_FOUND, WOMEN and FD_2 have been used as inputs.*

*Table n. 6 - DEA and SFA technical efficiency over the period 2008 2011 by university – Ranking of universities*

| *N.* | *Universities* | *DEA* | *N.* | *Universities* | *SFA (A)* |
|---|---|---|---|---|---|
| *1* | *Politecnico di Milano* | *0.8850* | *1* | *Università degli Studi "La Sapienza" - Roma* | *0.9827* |
| *2* | *Università degli Studi di Padova* | *0.8504* | *2* | *Università degli Studi di Bologna* | *0.9735* |
| *3* | *Università degli Studi "Cà Foscari" - Venezia* | *0.8446* | *3* | *Università degli Studi di Firenze* | *0.9577* |
| *4* | *Università degli Studi di Genova* | *0.8375* | *4* | *Università degli Studi di Padova* | *0.9481* |
| *5* | *Università degli Studi di Bologna* | *0.8306* | *5* | *Università degli Studi di Siena* | *0.943* |
| *6* | *Università degli Studi di Milano* | *0.8129* | *6* | *Università degli Studi di Milano* | *0.9408* |
| *7* | *Università degli Studi di Siena* | *0.8128* | *7* | *Università degli Studi di Torino* | *0.9377* |
| *8* | *Università degli Studi di Roma Tre* | *0.8092* | *8* | *Politecnico di Milano* | *0.9172* |
| *9* | *Università degli Studi di Torino* | *0.7823* | *9* | *Università degli Studi di Pisa* | *0.8841* |
| *10* | *Università degli Studi Gabriele D'Annunzio - Chieti e Pescara* | *0.7727* | *10* | *Università degli Studi "Federico II" - Napoli* | *0.8700* |
| *11* | *Università del Salento - Lecce* | *0.7703* | *11* | *Università degli Studi di Genova* | *0.848* |
| *12* | *Università degli Studi "L' Orientale" - Napoli* | *0.7639* | *12* | *Università degli Studi di Roma Tre* | *0.8317* |
| *13* | *Università degli Studi di Firenze* | *0.7585* | *13* | *Università degli Studi di Perugia* | *0.8151* |
| *14* | *Università Politecnica delle Marche- Ancona* | *0.7548* | *14* | *Venezia - Università IUAV* | *0.8148* |
| *15* | *Università degli Studi - Trieste* | *0.7483* | *15* | *Università degli Studi "Cà Foscari" - Venezia* | *0.8106* |
| *16* | *Università degli Studi di Pavia* | *0.7440* | *16* | *Università degli Studi di "Tor Vergata" - Roma* | *0.8041* |
| *17* | *Università degli Studi di Bari* | *0.7408* | *17* | *Università degli Studi di Pavia* | *0.7882* |
| *18* | *Università degli Studi - Palermo* | *0.7391* | *18* | *Università degli Studi - Trieste* | *0.7739* |
| *19* | *Università degli Studi di "Tor Vergata" - Roma* | *0.7367* | *19* | *Università degli Studi - Palermo* | *0.7584* |
| *20* | *Università degli Studi di Perugia* | *0.7358* | *20* | *Università degli Studi di Parma* | *0.7563* |
| *21* | *Politecnico di Torino* | *0.7294* | *21* | *Università degli Studi - Milano-Bicocca* | *0.7559* |
| *22* | *Università degli Studi - Milano-Bicocca* | *0.7291* | *22* | *Università degli studi di Catania* | *0.7461* |
| *23* | *Università degli Studi di Pisa* | *0.7219* | *23* | *Università degli Studi di Bari* | *0.7459* |
| *24* | *Università degli Studi di Bergamo* | *0.7161* | *24* | *Università degli Studi di Verona* | *0.7268* |
| *25* | *Università degli Studi di Cagliari* | *0.7088* | *25* | *Politecnico di Torino* | *0.7161* |
| *26* | *Università degli studi di Catania* | *0.7080* | *26* | *Università degli Studi - Udine* | *0.7134* |
| *27* | *Università degli Studi del Molise - Campobasso* | *0.7076* | *27* | *Università della Tuscia - Viterbo* | *0.7101* |
| *28* | *Università degli Studi "Federico II" - Napoli* | *0.7035* | *28* | *Università degli Studi di Modena e Reggio Emilia* | *0.7053* |
| *29* | *Università della Tuscia - Viterbo* | *0.6974* | *29* | *Università degli Studi di Cagliari* | *0.6890* |
| *30* | *Università degli Studi "Magna Grecia" - Catanzaro* | *0.6973* | *30* | *Università Politecnica delle Marche- Ancona* | *0.6771* |
| *31* | *Università degli Studi di Verona* | *0.6946* | *31* | *Università degli Studi Gabriele D'Annunzio - Chieti e Pescara* | *0.6729* |
| *32* | *Università degli Studi "La Sapienza" - Roma* | *0.6854* | *32* | *Università degli Studi di Ferrara* | *0.6623* |
| *33* | *Università degli Studi di Teramo* | *0.6816* | *33* | *Università degli Studi di Messina* | *0.6576* |
| *34* | *Venezia - Università IUAV* | *0.6733* | *34* | *Università del Salento - Lecce* | *0.6417* |
| *35* | *Università degli Studi di Parma* | *0.6557* | *35* | *Università degli Studi "L' Orientale" - Napoli* | *0.6292* |
| *36* | *Università degli Studi della Basilicata - Potenza* | *0.6522* | *36* | *Università dell'Insubria - Varese* | *0.6200* |
| *37* | *Università degli Studi - Udine* | *0.6242* | *37* | *Seconda Università degli studi di Napoli* | *0.6090* |
| *38* | *Università degli Studi di Modena e Reggio Emilia* | *0.6164* | *38* | *Università degli Studi di Bergamo* | *0.6033* |
| *39* | *Università degli Studi di Ferrara* | *0.6149* | *39* | *Università della Calabria - Arcavacata di Rende* | *0.5872* |
| *40* | *Università degli Studi di Messina* | *0.6137* | *40* | *Università degli Studi di Sassari* | *0.5819* |
| *41* | *Università degli Studi di Cassino* | *0.6092* | *41* | *Università degli Studi di Brescia* | *0.5742* |
| *42* | *Università della Calabria - Arcavacata di Rende* | *0.6068* | *42* | *Università degli Studi del Piemonte orientale "A. Avogadro"* | *0.5601* |
| *43* | *Università dell' Insubria - Varese* | *0.5866* | *43* | *Università degli Studi di Salerno* | *0.5586* |
| *44* | *Università degli Studi di Foggia* | *0.5760* | *44* | *Università degli Studi di Cassino* | *0.5378* |
| *45* | *Università degli Studi di Sassari* | *0.5757* | *45* | *Università degli Studi del Molise - Campobasso* | *0.5063* |
| *46* | *Seconda Università degli studi di Napoli* | *0.5707* | *46* | *Università degli Studi "Magna Grecia" - Catanzaro* | *0.4988* |
| *47* | *Politecnico di Bari* | *0.5654* | *47* | *Università degli Studi di Foggia* | *0.4862* |
| *48* | *Università degli Studi "Parthenope" - Napoli* | *0.5479* | *48* | *Università degli Studi di Teramo* | *0.4638* |
| *49* | *Università degli Studi di Salerno* | *0.5302* | *49* | *Università degli Studi "Parthenope" - Napoli* | *0.4593* |
| *50* | *Università degli Studi del Piemonte orientale "A. Avogadro"* | *0.5250* | *50* | *Università degli Studi Mediterranea - Reggio Calabria* | *0.4558* |
| *51* | *Università degli Studi di Brescia* | *0.5226* | *51* | *Università degli Studi della Basilicata - Potenza* | *0.4512* |
| *52* | *Università degli Studi del Sannio - Benevento* | *0.4544* | *52* | *Politecnico di Bari* | *0.4452* |
| *53* | *Università degli Studi Mediterranea - Reggio Calabria* | *0.4451* | *53* | *Università degli Studi del Sannio - Benevento* | *0.4224* |

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

*Table n.7 - 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*** | *0.063**** | *0.062**** | *0.154**** | *0.158**** | *0.158**** |
| | *(0.023)* | *(0.015)* | *(0.017)* | *(0.029)* | *(0.028)* | *(0.031)* |
| *FPS* | *-0.0001**** | *-0.0001**** | *-0.0001**** | *-0.0001**** | *-0.0009**** | *-0.0002**** |
| | *(0.00003)* | *(0.00003)* | *(0.00003)* | *(0.00005)* | *(0.00003)* | *(0.00004)* |
| *MK* | *-0.505**** | *-0.464**** | *-0.479**** | *-0.259* | *-0.210* | *-0.214* |
| | *(0.157)* | *(0.143)* | *(0.132)* | *(0.206)* | *(0.171)* | *(0.248)* |
| $MK^2$ | *0.319*** | *0.299*** | *0.313*** | *0.018* | *-0.006* | *-0.003* |
| | *(0.141)* | *(0.126)* | *(0.125)* | *(0.199)* | *(0.166)* | *(0.235)* |
| *YEAR_FOND* | *0.00007*** | *0.00006*** | *0.00005** | *0.00006* | *0.00006* | *0.00005* |
| | *(0.00002)* | *(0.00003)* | *(0.00003)* | *(0.00005)* | *(0.00004)* | *(0.00005)* |
| *WOMEN* | *4.62e-07* | *-4.25e-08* | *-9.40e-08* | *-3.57e-06*** | *-3.96e-06**** | *-4.25e-06*** |
| | *(1.17e-06)* | *(1.23e-06)* | *(1.06e-06)* | *(1.53e-06)* | *(1.37e-06)* | *(1.32e-06)* |
| *AV* | *-9.49e-07**** | | | *-1.06e-06** | | |
| | *(2.32e-07)* | | | *(6.35e-07)* | | |
| *FD_1* | | *-0.0007**** | | | *-0.0009**** | |
| | | *(0.0002)* | | | *(0.0003)* | |
| *FD_2* | | | *-0.001**** | | | *-0.001* |
| | | | *(0.0004)* | | | *(0.0008)* |
| *NORTHERN* | *-0.010* | *-0.016* | *-0.014* | *-0.011* | *-0.015* | *-0.017* |
| | *(0.024)* | *(0.023)* | *(0.022)* | *(0.048)* | *(0.048)* | *(0.036)* |
| *CENTRAL* | *-0.038* | *-0.042** | *-0.040*** | *-0.072* | *-0.073** | *-0.075** |
| | *(0.026)* | *(0.024)* | *(0.018)* | *(0.044)* | *(0.041)* | *(0.043)* |
| *T2* | *-0.020* | *-0.019* | *-0.019* | *-0.002* | *-0.001* | *-0.001* |
| | *(0.022)* | *(0.019)* | *(0.020)* | *(0.032)* | *(0.028)* | *(0.031)* |
| *T3* | *-0.107**** | *-0.108**** | *-0.107**** | *-0.065*** | *-0.066** | *-0.065*** |
| | *(0.025)* | *(0.022)* | *(0.022)* | *(0.034)* | *(0.036)* | *(0.028)* |
| *T4* | *-0.156**** | *-0.157**** | *-0.155**** | *-0.100**** | *-0.100**** | *-0.099**** |
| | *(0.025)* | *(0.020)* | *(0.023)* | *(0.035)* | *(0.032)* | *(0.030)* |
| *CONST* | *0.449**** | *0.449**** | *0.481**** | *0.359**** | *0.348**** | *0.384**** |
| | *(0.070)* | *(0.085)* | *(0.076)* | *(0.127)* | *(0.108)* | *(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 n.8 - 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 4st quartile* | | | *Without the 1st and the 4st quartiles* | | |
| *Variables* | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* | *(8)* | *(9)* |
| *MED* | 0.059*** | 0.064*** | 0.063** | 0.070** | 0.077*** | 0.076*** | 0.078*** | 0.085*** | 0.083** |
| | (0.020) | (0.021) | (0.024) | (0.028) | (0.028) | (0.028) | (0.027) | (0.030) | (0.035) |
| *FPS* | -0.0001*** | -0.0001*** | -0.0001*** | -0.00009* | -0.0008** | -0.0001* | -0.0001** | -0.0001*** | -0.0001* |
| | (0.00004) | (0.00003) | (0.00003) | (0.00005) | (0.00004) | (0.00005) | (0.00005) | (0.00004) | (0.00007) |
| *MK* | -0.450** | -0.416*** | -0.429*** | -0.625*** | -0.566** | -0.584*** | -0.635*** | -0.586** | -0.605** |
| | (0.176) | (0.122) | (0.136) | (0.205) | (0.255) | (0.210) | (0.224) | (0.246) | (0.259) |
| *$MK^2$* | 0.296* | 0.280** | 0.291** | 0.427** | 0.398* | 0.413** | 0.466** | 0.443** | 0.459* |
| | (0.158) | (0.112) | (0.120) | (0.181) | (0.238) | (0.189) | (0.196) | (0.220) | (0.236) |
| *YEAR_FOND* | 0.00006* | 0.00006* | 0.00005* | 0.00007 | 0.00007* | 0.00005 | 0.00007 | 0.00007 | 0.00006 |
| | (0.00003) | (0.00003) | (0.00003) | (0.00004) | (0.00004) | (0.00004) | (0.00005) | (0.00005) | (0.00006) |
| *WOMEN* | 8.74e-07 | 5.05e-07 | 4.43e-07 | -2.52e-07 | -9.50e-07 | -1.05e-06 | 7.48e-07 | 2.34e-07 | 9.67e-08 |
| | (1.32e-06) | (8.63e-07) | (1.08e-06) | (1.93e-06) | (2.05e-06) | (1.91e-06) | (1.80e-06) | (1.72e-06) | (1.57e-06) |
| *AV* | -7.97e-07*** | | | -1.41e-06*** | | | -1.22e-06*** | | |
| | (2.26e-07) | | | (4.87e-07) | | | (5.51e-07) | | |
| *FD_1* | | -0.0006*** | | | -0.001*** | | | -0.001** | |
| | | (0.0002) | | | (0.0003) | | | (0.0004) | |
| *FD_2* | | | -0.001** | | | -0.001** | | | -0.001** |
| | | | (0.0004) | | | (0.0008) | | | (0.0008) |
| *NORTHERN* | 0.004 | -0.001 | 0.001 | -0.036 | -0.043 | -0.045 | -0.013 | -0.020 | -0.021 |
| | (0.025) | (0.022) | (0.023) | (0.041) | (0.036) | (0.043) | (0.040) | (0.034) | (0.039) |
| *CENTRAL* | -0.021 | -0.024 | -0.022 | -0.057 | -0.062* | -0.062* | -0.034 | -0.038 | -0.038 |
| | (0.023) | (0.021) | (0.021) | (0.035) | (0.032) | (0.033) | (0.030) | (0.031) | (0.032) |
| *T2* | 0.001 | 0.002 | 0.003 | -0.034 | -0.033 | -0.033 | -0.009 | -0.009 | -0.008 |
| | (0.024) | (0.025) | (0.026) | (0.024) | (0.023) | (0.022) | (0.027) | (0.031) | (0.030) |
| *T3* | -0.084*** | -0.084*** | -0.083*** | -0.124*** | -0.125*** | -0.124*** | -0.100*** | -0.101*** | -0.100** |
| | (0.021) | (0.026) | (0.021) | (0.029) | (0.028) | (0.029) | (0.032) | (0.038) | (0.043) |
| *T4* | -0.133*** | -0.134*** | -0.132*** | -0.180*** | -0.182*** | -0.180*** | -0.162*** | -0.164*** | -0.162*** |
| | (0.020) | (0.028) | (0.027) | (0.031) | (0.026) | (0.033) | (0.034) | (0.039) | (0.054) |
| *CONST* | 0.407*** | 0.401*** | 0.434*** | 0.463*** | 0.465*** | 0.497*** | 0.426*** | 0.421*** | 0.461*** |
| | (0.094) | (0.105) | (0.073) | (0.110) | (0.108) | (0.080) | (0.124) | (0.132) | (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 4st quartile; Columns (7), (8) and (9) are associated with university efficiency scores without the 1st and the 4st quartiles.*
*All estimates are associated with bootstrapped university efficiency scores in the first stage (Double-boot DEA procedure).*

*Table n. 9 - SFA directional output distance – Variables affecting inefficiency*

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

*Figure n. 1 – Boxplots efficiency scores and Kernel density estimates*