Evaluating italian university teaching efficiency convergence: a non-parametric frontier approach

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Evaluating Italian University Teaching Efficiency Convergence: A Non-parametric Frontier Approach

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Abstract

The *Bologna Process* promoted a wide-ranging reform of High Education systems in order to improve teaching activities throughout Europe. This paper evaluates the effect of these reforms on teaching efficiency of the Italian universities in the period 2000-2010. We employ the bootstrapped Data Envelopment Analysis (DEA) algorithm to evaluate efficiency and then examine convergence using several panel data estimators. We find evidence of convergence but technical efficiency increased mainly in the first period of implemented reform. Moreover, we find strong evidences of persistence of gaps both between regions and universities.

Keywords: HEI, Bologna process, teaching efficiency, β-convergence, DEA.

JEL Code: D24, I23

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1. Introduction

The Bologna Declaration signed in 1999 by European ministers for Education opened a period of reforms of Higher Education (HE) systems that aimed at creating a common European Higher Education Area (EHEA) and implementing proper policies in order to improve the quality of courses of studies, enhance the competitiveness of European higher education institutions and make academic institutions more attractive for students and staff both within Europe and from other continents. The harmonization aspects of the *Bologna Process* (hereafter, BP) in EU education programmes was also relevant of higher education processes and structures and several European countries have undertaken reforms of the University system aimed at the development of an integrated and coherent European Higher Education Area (EHEA). However, we still have rather limited knowledge on the extent to which the BP actually led to the convergence of national higher education institutions since BP has had different implications across countries.

The higher education sector in Italy, for example, has undergone a reform process, since 1999, to align itself with the European model outlined through the BP. The Italian HE system is one of the biggest in EU and it is also characterized by a structural internal heterogeneity and a relevant geographical gap along the North-South axis (Agasisti and Dal Bianco, 2006; 2009). In such a contest the implementation of the reform have largely interpreted as a mean to increase enrolment, reduce drop-out rates, improve equality of opportunities for access to university, and promote the performance of HE institutions. Thus, after more than a decade since the *BP*, we believe that it is important to evaluate the overall effect that BP implementation had on teaching activities. Specifically, the paper analyses the impact of these reforms on teaching efficiency of the Italian universities in the period 2000–2010 employ a bootstrapped Data Envelopment Analysis (DEA) algorithm to evaluate efficiency in a first stage and then examine convergence using the β and *σ* convergence methods. Moreover, we focus on a homogeneous institutional setting rather than the whole international sample to better control for the presence of parameter heterogeneity and measurement error problems.

More in particular, the aim of this paper is threefold. Firstly, we want to evaluate how Italian Higher Education Institutions (HEIs)' average teaching efficiency varied in the considered period, that is whether HE system moved to higher or lower efficiency levels. We estimate universities' teaching efficiency by means of DEA using data collected by Italian National Evaluation Committee (*Comitato Nazionale per la Valutazione del Sistema Universitario,* CNVSU) on the same line of Agasisti and Dal Bianco, (2009). With respect to previous studies, we analyze technical efficiency on a longer period (2000-2010) and employ a smoothed DEA bootstrap procedure that ensures consistency of our efficiency estimates (Simar and Wilson, 2000).

Secondly, we differ from previous research in introducing the concepts of unconditional *β-convergence* and *σ-convergence* of technical efficiency (Weill, 2009; Casu and Girardone, 2010; Zhang and Matthews, 2012; Ayadi et al., 2013), in order to assess whether the reform process resulted in an efficiency gain and a convergence of Italian HEIs to the frontier of best practice.

Finally, we investigate whether the reform weakened or not the structural geographical gap between regions[1].

To provide robustness to our findings, we also employ several checks by comparing results obtained under different assumptions and specifications, re-estimating teaching efficiency through parametric methods (SFA) and on subsamples.

Our empirical results show that Italian teaching efficiency increased only in the first period of implemented reform and then started to decrease weakly. Moreover, the reform was effective in enhancing universities' convergence in terms of teaching efficiency. Finally, we find evidences of persistence in inefficiency gaps among geographical areas and universities.

The remainder of the paper is organized as follows: in the next section we provide a brief overview on reform processes employed starting by the end of 90s. Section 3 reviews the related literature. Section 4 describes the methodological framework and data. Section 5 includes our findings and robustness checks. Finally, section 6 presents few concluding remarks.

2. The Bologna Process and the Italian higher education system

2.1 The higher education reform in Europe

The BP was launched in 1999 when Ministers responsible for higher education from 29 European countries[2] signed the Bologna Declaration in order to put in motion a wide ranging reform of higher education in Europe. The crucial aim of

[1] There is a large literature showing a duality in the Italian socio-economic system between the developed North-Centre and the less-developed South, also in human capital endowments (Di Liberto, 2008).

[2] At present, the Bologna Process involves 47 Countries.

the statement was the creation of a common EHEA and the consequent implementation of policies to improve the quality of study courses, enhance the competitiveness of European HEIs and make academic institutions more attractive for students and staff both from Europe and other continents.

The key objectives pursued by the reform process involved the implementation of a two-cycle structure of degrees (undergraduate/graduate), the establishment of a credit point system based on the European Credit Transfer and Accumulation System (ECTS) for the assessment of study performance, the adoption of a system of comprehensible and comparable degrees, the promotion of mobility both of students and academic staff, the development of shared criteria on quality control, the promotion of a European dimension in higher education.

The implementation of the Bologna Declaration was supported by the adoption of a series of policies to allow the convergence across European HE systems (Huisman and Van der Wende, 2004). Trends show that this goal was reached in general (Witte et al., 2009).

With respect to the enhancement of student participation, empirical analyses indicate that the reform process has improved overall participation rates in higher education, showing a movement toward a 'massification' of higher education system (Crosier et al., 2012), even though differences across countries and disciplines still exist (Sursock and Smidt, 2010). Moreover, countries such as the Netherlands, Scotland and Sweden have implemented policies to widen participation involving also immigrants and ethnic minorities (Sursock and Smidt, 2010).

Further, public authorities have reduced the amount of financial resources assigned to universities and promoted a higher degree of autonomy of HEIs. As a result, academic institutions have to compete in order to find alternative source of funding and are forced to increase efficiency in teaching and research (Aghion et al., 2010; Bergantino et al., 2013), as well as differentiate themselves in terms of range of outputs they produce (Olivares and Wetzel, 2011).

Considering the radical changes that BP prompted in European HE systems, the evaluation of the consequences in terms of universities' efficiency after more than ten years from the reform is needed, and in fact it has been recently explored over several dimensions and for different countries (Cardoso et al., 2008; Agasisti and Dal Bianco, 2009; Cappellari and Lucifora, 2009; Di Pietro, 2011; Sciulli and Signorelli, 2011; Agasisti and Bolli, 2013; Bergantino et al., 2013).

2.2 The reform of the Italian HE system

The main target of the BP was to enhance the European standard for Higher education that, as a consequence, would in principle involve a process of convergence of HEIs performance towards higher levels. However, a substantial heterogeneity in the BP implementation throughout Europe has prevented a comprehensive study of the overall effect on all HE systems.

In order to investigate this issue and the extent of convergence determined by the BP, we refer to the Italian HE system, which is one of the largest and least efficient in Europe (Lambert and Butler, 2006) and it is furthermore characterized by a substantial geographical heterogeneity (Agasisti and Dal Bianco, 2009; Agasisti and Pohl, 2012). The implementation of BP principles in Italy have been assessed in 1999 through the introduction of both a system of internal evaluation and data collection and a new organization of courses[3].

The system of internal evaluation was established (Law no. 370/99) through the institution of university level evaluation offices (*Nuclei di Valutazione –NdV*) which collect data for each institution, and a National Evaluation Committee, the *Comitato Nazionale per la Valutazione del Sistema Universitario* (CNVSU) which defines general criteria of evaluation and carries out annual reports on both teaching and research performance (Agasisti and Catalano, 2007).

Successively, the Law no. 509/99, implemented from the academic year 2001-02 onwards, introduced a greater flexibility in the study programs in order to accelerate the progression and completion of studies. Moreover, this law reformed the organization of courses and granted academic institutions the authority of establishing the content of courses they offer. The new 3+2+3 model is now organized around three levels: a first degree (*Laurea triennale*) of 3 years, followed by a second degree (*Laurea specialistica*) of 2-years length. Students in possession of a second level can then access to the PhD programs (*Dottorato di ricerca*), lasting 3 years.

3. Efficiency evaluation of HEIs: a literature review

Efficiency of higher education institutions has been largely explored in the last decades as a result of an increasing interest in improving the performance of public sector and no-profit institutions.

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[3] The Italian HE system has experienced a deep and unsystematic process of reform over the last decades. The reform process started in the late 80s, with the introduction of the self-regulation principle in 1989 and of HEIs financial autonomy in 1993 in line with the general trend of European university sector system in favor of decentralization. More recently, the so-called *Gelmini Reform* (Law no. 240/2010) further modified Universities' internal organization.

Using parametric and non-parametric techniques, extensive empirical evidence has been produced focusing on higher education institutions performance. Most studies adopt non-parametric frontier techniques such as DEA since, in spite of some limitations, it allows for analyzing efficiency of multiple-input-multiple-output processes and moreover it does not require a specific functional form for the production function. This is considerably advantageous when properties of the production function are not obvious (Johnes, 2006).

Early researches on this issue focus on homogeneous departments in a given discipline since they are supposed to have analogous structures (Tomkins and Green, 1988; Beasley, 1990; 1995; Dundar and Lewis, 1995; Madden et al., 1997; Bergantino et al., 2013) and most of them have been conducted on UK universities (*e.g.*: Johnes and Johnes, 1995, studying efficiency of economics departments in 36 British universities in 1989; Beasley, 1995, exploring efficiency of chemistry and physics departments in 1992).

More recently, several studies investigate efficiency of single universities in a dynamic perspective by employing panel data methods. Athanassopoulos and Shale (1997) study 45 British universities for the years 1992-1993; Flegg et al. (2004) study 45 British universities in the period 1981-1993; Kempkes and Pohl (2010) examine 72 German universities for the period 1998-2003.

Another recent strand of researches compares efficiency of universities across different European countries: Agasisti and Johnes (2009), Agasisti and Pérez-Esparrells (2010) and Agasisti and Pohl (2012) respectevely compare Italian universities with British, Spanish and German ones.

Several works found evidences of efficiency gaps within countries: Agasisti and Dal Bianco (2006, 2009) state that universities in the Northern part of Italy outperform those located in the South; Agasisti and Pohl (2012) study teaching and research efficiency in Italy and Germany between 2001 and 2007 and state that regional gaps in Italy - along the North-South axis - and in Germany – along the West-East axis – have been reduced in the considered period. Agasisti e Dal Bianco (2009), on the other hand, study teaching efficiency in Italy in the period 1998/1999 – 2003/2004 and use Malmquist Index in order to investigate the pattern of efficiency in the period 2000-2003. Results show a divergence in terms of efficiency. At the best of our knowledge, Agasisti and Dal Bianco (2009) and Agasisti and Pohl (2012) are the only ones that attempt to investigate efficiency in terms of convergence/divergence with respect to higher education institutions.

A debatable issue in efficiency studies is the selection of a proper set of inputs and outputs of the production process. In general terms universities are complex entities that 'produce' graduates, researches and related services by using workers who belong to academic (researchers and teachers) and non-academic staff, financial resources and facilities. The number of enrolled students as well as both the academic and administrative staff are widely used as inputs in the large majority of studies (Abbot and Doucouliagos, 2003; Johnes, 2006; Sav, 2012; Wolszczak-Derlacz and Parteka, 2011; Kantabutra and Tang, 2010; Johnes, 2008; Agasisti and Dal Bianco, 2009). Moreover, financial measures such as current expenditures are commonly used (Johnes, 2008; Johnes and Yu, 2008) in addition to a proxy of physical inputs, such as the number of available places in teaching rooms and libraries (Athanassopoulos and Shale, 1997; Johnes and Yu, 2008;

Agasisti and Dal Bianco, 2009). Few studies take also into account the quality skills of enrolled students (Agasisti and Dal Bianco, 2009).

As for the output, the literature on universities' efficiency underlines the lack of appropriate measures of quality, in terms of teaching and research outcomes. Because our interest here is on teaching activities we discuss this stand of literature[4]. Most studies analyzing universities' teaching efficiency focus on teaching-based measures of output such as the number of graduates (*e.g.*: Agasisti and Pérez-Esparrells, 2010; Wolszczak-Derlacz and Parteka, 2011; Kantabutra and Tang, 2010; Johnes, 2008). However, such a measure does not reflect the quality of education so leading to potentially biased efficiency scores in favor of high-output-low-quality universities. With respect to this issue, Johnes (2006) uses the number of graduates weighted by their degree classification, Kuah and Wong (2011) include graduates' results, universities' graduation rates and graduates' employment rates, Joumady and Ris (2005) use students' self-reported acquired competences, Bergantino et al. (2013) employ the on-time graduation index (*i.e.* the ratio between the number of years scheduled for each degree course and the average number of years of delay). Finally, Agasisti and Dal Bianco (2009) include the number of regular student (*i.e.* the students who carry out the degree within the expected time schedule).

Overall, there is very limited empirical evidence on the efficiency convergence of higher education institutions. Hence, with this paper we aim to provide some first findings on teaching efficiency of Italian HE system in terms of convergence after

[4] The studies that focus on research activities use as output indexes related to HEIs prestige (Johnes and Yu, 2008), external resources attracted to research activities (Johnes, 2008; Agasisti and Pérez-Esparrells, 2010), number of published works and citations (St. Aubyn et al., 2009) and the number of PhD degrees.

several years from the Bologna Process that aimed at increasing teaching efficiency and enhance a high level European standard for HE.

4. Methods and data

4.1 Methodological framework

In this study, on the same line of Agasisti and Dal Bianco, (2009), we focus on teaching efficiency of Italian higher education institutions (our Decision Making Units - DMUs), which involves the comparison of the actual performance of each DMU with the optimal performance of DMUs located on the relevant frontier (*i.e.* the best practice frontier). This approach is based on the efficiency measures proposed by Koopmans (1951) and Debreu (1951) and empirically applied by Farrell (1957). Two main analytical approaches are available to estimate efficiency frontiers: parametric frontier and non-parametric frontier[5].

In this paper, we apply the non-parametric frontier method developed by Charnes et al. (1978) that generalized Farrell's single input/output measure to a multiple-input/multiple-output technique. The aim of this approach is to measure productive efficiency through the estimation of a frontier envelopment surface for all DMUs by using linear programming techniques. By constructing envelopment unitary isoquants corresponding to comparable DMUs across different situations, DEA identifies as productive benchmarks those DMUs that exhibit the lowest technical coefficients, *i.e.* the lowest amount of inputs to produce one unit of output. In so doing, DEA allows for the identification of best practices and for the comparison of each DMU with the best possible performance among the peers,

[5] For a more extensive discussion, see Cooper et al. (2007) and Fried et al. (2008).

rather than just with the average. Once the reference frontiers have been defined, it is possible to assess the potential efficiency improvements available to inefficient DMUs if they were producing according to the best practice of their benchmark peers. From an equivalent perspective, these estimates identify the necessary changes that each DMU needs to undertake in order to reach the efficiency level of the most successful DMU.

Following the literature reviewed in the previous section we employ an output-oriented approach[6]

In order to facilitate the interpretation of the results in the next sections, it is useful to recall that in the output-oriented DEA model, considering *n* DMUs to be evaluated, an efficiency score θ_i is calculated for each DMU by solving the following program, for $i=1,\ldots, n$, in the case of constant returns to scale (CRS):

$$
\begin{aligned}
& Max_{\lambda,\theta_i}\, \theta \\
& s.t.\ x_i \geq X\lambda \\
& \theta_i y_i \leq Y\lambda \\
& \lambda \geq 0
\end{aligned}
\qquad (1)
$$

where x_i and y_i are, respectively, the input and output of *i-th* DMU; X is the matrix of inputs and Y is the matrix of outputs of the sample; λ is a $n\times 1$ vector of weights which allows to obtain a convex combination between inputs and outputs. Solving (1), DMUs with an efficiency score equal to one are located on the

[6] From an output-oriented perspective efficiency is defined as the ratio of a DMU's observed output to the maximum output which could be achieved given its input levels(Farrell, 1957).

frontier and therefore their outputs cannot be further expanded without a corresponding increase in inputs[7].

Banker et al. (1984) modified the model (1) to account for variable returns to scale (VRS) by adding the convexity constraint: $e\lambda=1$, where e is a row vector with all elements unity, which allows to distinguish between Technical Efficiency (TE) and Scale Efficiency (SE).

Notwithstanding their large use, DEA estimators have received some criticism since they rely on extreme points, and they could be extremely sensitive to data selection, aggregation, model specification, and data errors (Simar and Wilson, 2008)[8]. However, to account for DEA traditional limitations, which do not allow for any statistical inference and measurement error, Simar and Wilson (1998, 2000) introduced a bootstrapping methodology to determine the statistical properties of DEA estimators. The idea underlying the bootstrap procedure is to approximate the sampling distributions of efficiency scores by simulating their Data Generating Process - DGP (Simar and Wilson, 2008).

Thus, to overcome traditional DEA limitations and to provide a robustness check of our findings, we employ a consistent bootstrap estimation procedure (Simar and Wilson, 1998), to obtain the sampling distribution of the efficiency scores and derive bias corrected scores.

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[7] In the first stage of this analysis, we assume an output-oriented model to maximize the outputs that could be produced given the inputs. Moreover, we assume a Shephard (1970) output-oriented distance function and, consequently, efficiency scores assume values between zero and one, that is the reciprocal of Farrell (1957) distance function.

[8] Alternative approaches do exist to provide robust measures of efficiency at extreme data points based on partial frontiers and the resulting partial efficiency scores. A detailed survey of these approaches can be found in Simar and Wilson (2008). See also Wilson (2012) for a discussion on these approaches and for a proposed extension of *order-m* estimator obtained by Cazals et al. (2002).

4.2 Convergence of HE systems

While a large amount of studies on higher education institutions efficiency, reviewed in Section 3, have investigated efficiency gains and losses and their determinants, the aim of this study is also to evaluate Italian University system in terms of convergence over the period 2000-2010. To do so, we use the concepts of unconditional *β-convergence* and *σ-convergence* that have been widely applied in the growth literature during the last decade since the seminal paper by Barro and Sala-i-Martin (1991; 1992).

This approach has been used also in the efficiency frontier literature mainly in the banking sector (Weill, 2009; Casu and Girardone, 2010; Zhang and Matthews, 2012; Ayadi et al., 2013). To the best of our knowledge this is the first study applying this framework to HE in order to investigate convergence in technical efficiency of Italian universities.

More in detail, we investigate whether universities converged in terms of teaching efficiency over the period 2000-2010 (unconditional *β-convergence*). Then, we study cross-sectional dispersion, *i.e.* how quickly each university converges toward the average efficiency (*σ-convergence)*; finally we employ a simple Partial Adjustment Model (PAM) in order to evaluate persistence in inefficiency. Moreover, because previous studies have detected a North-South gap in terms of efficiency (Agasisti and Dal Bianco, 2009; Monaco, 2012) we evaluate the convergence both at university and at regional level.

In the first step estimates, we employ both efficiency scores θ and bias corrected efficiency scores $\hat{\theta}$ using bootstrap estimation algorithm proposed by Simar and Wilson (1998) to take into account that efficiency scores are sensitive to outliers and upward biased by construction. Thus, to estimate unconditional *β-convergence* we employ the following model:

$$\Delta\hat{\theta}_{i,t} = \alpha + \beta\left(\ln \hat{\theta}_{i,t-1}\right) + \rho\Delta\hat{\theta}_{i,t-1} + \epsilon_{i,t} \qquad (2)$$

where $\hat{\theta}_{i,t}$ is the bias corrected efficiency score of university i at time t, $\Delta\hat{\theta}_{i,t}$=ln $\hat{\theta}_{i,t}$-ln $\hat{\theta}_{i,t-1}$ and $\epsilon_{i,t}$ is the error term and β is the convergence parameter. In this framework, a negative value of β implies convergence.

Moreover, we estimate the equation by (i) pooled OLS, (ii) pooled OLS including the lagged dependent variable, (iii) Fixed Effect (FE) in order to capture individual specific effect, (iv) SYS-GMM in order to deal with potential endogeneity[9].

To estimate how quickly each university's efficiency converges to the mean, we employ the following autoregressive distributed lag model:

$$\Delta E_{i,t} = \alpha + \sigma E_{i,t-1} + \rho\Delta E_{i,t-1} + \epsilon_{i,t} \qquad (3)$$

where $E_{i,t}$=ln $\hat{\theta}_{i,t}$-ln $\bar{\hat{\theta}}_{t}$; $E_{i,t-1}$=ln $\hat{\theta}_{i,t-1}$-ln $\bar{\hat{\theta}}_{t-1}$; $\Delta E_{i,t} = E_{i,t} - E_{i,t-1}$; $\bar{\hat{\theta}}_{t}$ is the mean of efficiency scores $\hat{\theta}$ of all universities at time *t,* $\epsilon_{i,t}$ is the error term and σ is the convergence parameter to be estimated that represents the rate of convergence. Once again, we perform estimations at both university and regional levels and by OLS, OLS with lagged dependent variable, FE and by GMM.

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[9] To select the appropriate estimation model we perform F-test on fixed effects and the Hausman specification test for appropriate common effect model (see Table A.3 in the appendix).

Finally, we consider a setup where universities tend to reach the full efficiency by adjusting their performance towards the best practice frontier. For this purpose, we employ the following PAM equation:

$$\ln\hat{\theta}_{i,t} - \ln\hat{\theta}_{i,t-1} = \gamma\left(\ln\hat{\theta}_{max} - \ln\hat{\theta}_{i,t-1}\right) \quad (4)$$

where y_{max} is the best practice, *i.e.* the target each university would reach, that is unity, and γ is the adjustment parameter that defines the proportion of gap to be filled each period. By substituting $k = 1 - \gamma$ the resulting model that we estimate by OLS and FE on both the two samples is:

$$\ln\hat{\theta}_{i,t} = k\left(\ln\hat{\theta}_{i,t-1}\right) \quad (5)$$

where $\hat{\theta}_{i,t}$ is still the efficiency score of university i at time t, and k captures the persistence of $\hat{\theta}_{i,t-1}$ on $\hat{\theta}_{i,t}$.

Our aim, in this step, is to compare persistence of inefficiency at university and regional level in order to verify whether HE reforms weakened not only the gap between universities but also, that is more relevant in our opinion, the efficiency gap between regions, which is whether reforms succeeded in reducing the structural geographical gap that affected Italian HE system.

4.3 Data

The dataset we use is drawn from CNVSU database that includes data on each university institution collected on yearly basis by *Nuclei di Valutazione*. Data have been analyzed for reporting errors, outliers and missing values and refer to the academic years 2000-2001 to 2010-2011. As, in general, recently established universities are characterized by a higher output/input ratio since they do not need to immediately fulfill teaching and facilities requirements, we have included in the sample only those institutions that were fully operative in the academic year 2000-2001 (*i.e.* they have completed at least a first round of the degree programs)[10].

Therefore, the resulting dataset consists of a sample of cross-sectional and time series observation for 69 Italian institutions both public and private for 11 years, thus resulting in 759 observations.

Although Universities are complex multi-output institutions, we focus on teaching activities since the increase of graduates as well as the reduction of students' career time have been considered as key targets of university system reforms. As a result, our simplified framework considers universities as DMUs that use academic staff, students and facilities in order to 'produce' graduates (Agasisti and Dal Bianco, 2009).

When selecting inputs and outputs for the first stage of our analysis, we followed the example of other studies that have developed DEA frameworks for measuring HEIs efficiency. Thus, in our first simplified model (*mod 1*) we employ the total number of students (STUD) the total number of academic staff (AS) and the total number of available places in teaching rooms, libraries and laboratories (STR), as inputs and the total number of graduates (GRAD) as an output.

[10] However in the considered period new HEIs (especially online universities) have been established. The results we present in the following sections are also robust with respect to the full unbalanced sample including all universities that completed at least a first round of degree programs.

As a robustness check and to take into account for quality aspects of teaching production, following the suggestion by Agasisti and Dal Bianco (2009), we consider an alternative specification (*mod 2*) that includes: the number of enrolments with a score equal or greater than 9/10 in secondary school in the input set, as a proxy for the quality of new students (ENR_9); the total number of regular graduates (GRAD_R) as a proxy for output quality[11]. Table 1 summarizes the employed variables and reports the descriptive statistics[12].

- TABLE 1 around here –

5. Results and discussion

As we previously mentioned, the aim of our study is the evaluation of the effects of the BP reforms on the teaching efficiency of Italian HEIs. The analysis we perform in this section is threefold. We are firstly interested in verifying whether on average the reform resulted in an efficiency gain for Italian HE system. Then, we test the hypothesis of convergence and, finally, we assess whether and to what extent the reform weakened geographical gaps.

[11] As previously stated, the choice of both inputs and outputs strictly depends on the availability of data and we are perfectly aware that the set of variables we include does not allow us to capture quality directly. However, we have included both ENR_9 and GRAD_R in order to reflect the qualitative aspect of teaching efficiency that has been considered explicitly as a key issue in HE reforms in Europe.

[12] More statistical details can be found in Table A.1 in the Appendix.

In what follows, we used an output-oriented approach for computing the DEA frontier[13] that is frequently used in the context of HEIs efficiency, as we report in Section 3[14].

By means of DEA we may measure universities' efficiency with respect to either a unique frontier estimated by pooling the data (*intertemporal* frontier approach) or separately by estimating a frontier for each year (*contemporaneous* frontiers approach)[15]. The former allows us to estimate efficiency scores by using the same benchmark and enable us to assess the pattern of efficiency over time[16]. Moreover, as observed by Zhang and Matthews (2012, p. 1468), "as a general rule, efficiency levels measured relative to one frontier cannot be directly compared with efficiency levels measured relative to another frontier". For these reasons we focus on *intertemporal* frontier estimates. However, we provide *contemporaneous* frontier estimates in section 5.4 as a robustness check of our empirical findings.

Finally, to control for sampling variation, we use a bootstrap procedure with 2,000 iterations developed by Simar and Wilson (1998) to correct the DEA estimate bias and generate confidence intervals.

Table 2 provides summary statistics on the estimated efficiency scores by year and for different assumptions with respect to: model specification (*mod 1* and *mod 2*), returns to scale (CRS and VRS) and bias correction.

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[13] With respect to the first step, technical efficiency has been estimated with the software package FEAR 1.15 (Wilson, 2008)), while equations (2), (3) and (5) have been estimated with Stata v.11.2 SE.

[14] The output oriented approach is generally preferable in this setting because the quantity and quality of inputs, such as enrollment student and personnel, are assumed to be fixed exogenously, at least in the short term. However, our main results hold even under the input-oriented approach.

[15] See Jondrow et al. (1982).

[16] Moreover, time invariant technology is assumed when estimating *intertemporal* frontier.

- TABLE 2 around here -

Overall, the table indicates a relatively poor average performance of Italian universities. Indeed, the average overall efficiency score for HEIs over the whole sample period is 46.37%, indicating a 53.63% average potential improvement in outputs. However, it appears to be higher when measured by production functions that control for quality (*mod 2*). Nevertheless, this result is expected due to the 'curse of dimensionality' that affects DEA estimator (Kneip et al., 1998)[17].

These estimates are comparable to previous findings available in the literature (Agasisti and Dal Bianco, 2009) considering that we use a common frontier[18]. The yearly results seem to indicate an efficiency gain mainly in the first years of the analysis.

Lastly, a debatable issue in HEIs efficiency studies concerns returns to scale in production. Since our interest here is to evaluate only teaching activity, CRS can be reasonable assumed[19].

Due the abovementioned considerations, our benchmark analysis is based on CRS bias corrected efficiency scores estimated according to both *mod 1* and *mod 2*, where DMUs are compared with respect to the common *intertemporal* frontier.

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[17] The curse of dimensionality implies that the relative small number of DMUs with respect to the dimensionality space, (i.e. the number of input and output variables in the efficiency analysis), tends to automatically produce higher estimates for the efficient frontier. For a numerical example of the trade-off between sample size and number of inputs and outputs used, see Simar and Wilson (2008, p. 439).

[18] For an evaluation of the efficiency estimates using *contemporaneous* frontier see also Table 6.

[19] Nevertheless we performed the Banker (1996) test for *mod 1* and the results show that we cannot reject the null hypothesis of CRS at conventional level of significance. Results are available upon request.

5.1 The efficiency gain of the BP reform

We can focus the attention on the bias corrected CRS scores estimated by pooling the data (*intertemporal frontier*) to assess the gain of efficiency in the observed period.

- FIGURE 1 around here -

Figure 1 reports average values by year of abovementioned estimates. By looking at *mod 1* and *mod 2* average values, we can conclude that average efficiency significantly increased after 2002 and later decreased after 2005. We interpret this trend in connection with the conclusion of the new first-cycle degrees. It can be explained by considering the shorter length of the new courses as well as the fact that in the very first years after the reform a considerable share of un-regular students enrolled for the new courses without losing the credit achieved so far, so boosting the number of graduates. When this boosting effect exhausted, the average efficiency started to decline again. However, this shift from old to new courses positively affected the ratio of regular graduates, as it can be seen by *mod 2,* and weakened the decreasing pattern of efficiency in the last part of the observed period (Figure 1).

Hence, previous results state that the efficiency gain has taken place only in the first years of BP reform.

The same result can be viewed by plotting the density of CRS bias corrected scores for some selected years and, more in detail, for the first, the turning point (2005) and the last year. In Figure 2, relatively to abovementioned years, we report the univariate kernel smoothing distribution (Wand and Jones, 1995) and the reflection method to determine densities for the performance estimates. The criterion for bandwidth selection follows the plug-in method proposed by Sheather and Jones (1991).

This plot allows us to confirm the pattern of efficiency in the considered period and moreover provides a preliminary result in terms of convergence. It clearly shows that, the differences in efficiency levels (evidenced by a reduction in the thickness of the tails) declined constantly in the period.

- FIGURE 2 around here -

5.2 Convergence of Italian HEIs efficiency

As we have previously stated, the creation of a common EHEA implies a process of convergence in terms of efficiency. In order to evaluate the overall effect of the BP on the Italian HE system, we are now interested in testing the *β-convergence* hypothesis over the period 2000-2010 by estimating equation (2) by OLS, OLS with lagged dependent variable[20], DMUs FE and SYS-GMM to address potential endogeneity problem. In Table 3, we provide our estimates with respect to CRS-bias corrected scores for both *mod 1* and *mod 2*. The estimated *β* parameter is negative and strongly significant across both specifications[21] indicating that convergence occurred in the observed period; that is, low efficient universities increased their level at a higher speed.

[20] We apply the Banker and Natarajan procedure (2008) for estimate the unconditional *β-convergence* and *σ-convergence* by robust OLS.

[21] Though AR(1) tests for SYS-GMM, which can be provided at request, show a poor goodness of fit.

- TABLE 3 around here -

Table 4 shows *σ-convergence* estimates [equation (3)] for both *mod 1* and *mod 2* CRS bias corrected efficiency scores. *σ-convergence* refers to a reduction of the dispersion in levels. A negative sign implies convergence in this sense while the absolute value of parameter σ returns a measure of speed. Results reported in Table 4 confirm a reduction of dispersion in the considered period.

- TABLE 4 around here -

5.3 Persistence of inefficiency gap

As previously indicated, Italian HE system was characterized by a relevant geographical gap along the North-South axis (Agasisti and Dal Bianco, 2009). In this section, we evaluate persistence of inefficiency between both universities and geographical areas in order to assess whether the BP was effective in reducing such a gap.

A preliminary graphical analysis can be carried out by plotting average CRS bias corrected efficiency scores with respect to geographical areas (respectively the Centre-North, the South of the country)[22] and for all sample. Figure 3 and 4 show the pattern of efficiency scores for the considered period and for both the specifications (*mod 1* and *mod 2*).

- FIGURE 3 around here -

[22] More statistical details can be found in Table A.2 in the Appendix.

- FIGURE 4 around here -

Graphical inspection of the two figures shows a common trend in efficiency but with a lag in the turning point for the South compared to the full sample. This result could be connected to the delayed implementation of the new degree cycles in the South of Italy.

Looking at Figure 3, the efficiency gap started to decrease at the turning point. Thus, as soon as average universities' scores started to decline, the two areas slightly diverged. However, the latter effect does not hold when considering also the qualitative aspect in efficiency evaluation (Figure 4), wherein convergence occurred also after 2006.

To better evaluate the persistence of inefficiency gap, we employ the PAM described by equation (4). We firstly study persistence at university level and then move to the evaluation of the geographical gap. Since the cross-section dimension of classical geographical areas do not allow to perform the estimation, we work on regional levels.

In Table 5, we present estimation results with respect to equation (4) for *mod 1* and *mod 2* estimated on the basis of CRS bias corrected scores and compare university and regional level persistence.

We do so in order to verify whether the persistence of the gap between regions is (or not) higher than between universities, in which case we should conclude that reforms failed (succeeded) in reducing the structural gap that existed before the reform started.

In general, inefficiency is relatively persistent both at university and regional level. However, looking at FE estimates, persistence is slightly higher between regions than universities. It would indicate that reforms were not effective in reducing the gap in the observed period, although the F-test on regional fixed effects fails.

Such results lead us to conclude that although a process of convergence occurred at university level we cannot empirically support the hypothesis that regional gaps have been weakened in the considered period.

- TABLE 5 around here -

5.4 Robustness checks

To verify the reliability and robustness of our results, we conducted some further tests to control for potential pitfalls in previous findings.

First, one may argue that a better empirical strategy was to employ a *contemporaneous* frontiers approach by estimating the efficiency scores for each year (as suggested by Casu and Girardone, 2010) since *intertemporal* frontier approach does not allow for the identification of year-specific effects and moreover it requires time invariant assumptions on the HEIs production process.

For this purpose, we re-estimated efficiency scores on yearly basis. Table 6 shows the results from *mod 1* and *mod 2* based on the full sample.

- TABLE 6 around here -

We remind that non-parametric estimators, such as DEA, suffer from the 'curse of dimensionality' (Kneip et al., 1998), that is, efficiency scores tend to be upward biased as much as the number of DMUs is relatively low compared to the dimensionality space (see footnote 15). As a result, the *contemporaneous* frontiers estimates tends to strengthen the upward bias. Indeed, efficiency scores estimated through *contemporaneous* (yearly) frontiers are far higher than those estimated by pooling all the data, as we can see by comparing Table 2 and Table 6. Moreover, since *contemporaneous* frontiers DEA estimates could suffer for year-specific unobserved effects, time fixed effects should be taken into account in convergence estimates.

We provide in Tables 7 to 9 convergence estimates relative to efficiency scores derived from *contemporaneous* frontiers. Overall, our previous results seem to hold.

- TABLE 7 around here -

- TABLE 8 around here -

- TABLE 9 around here -

Second, it is important to assess whether the case selection in terms of HEIs plays a role in the results previously attained. Therefore, we considered the subsample of universities that have been established before the year 1997[23]. Again, the results confirmed the robustness of the main findings of the analysis[24].

Finally, we re-run our efficiency estimates by employing the SFA approach, as an alternative to DEA, to examine the efficiency of HEIs[25]. Following Weill (2009)s'

[23] As a result, the subsample includes only institutions that have been established before the 1998-2000 three-years programming period.

[24] The results of these estimates are not reported here but are available from authors upon request.

[25] Following well-established conventions in the literature, we estimate a Cobb-Douglas production function with half-normal distribution and we employ an input distance function to make it more comparable to DEA estimates.

approach, we used these efficiency estimates to evaluate the convergence. Estimates substantially confirm main results[26].

Overall, the current empirical analysis stated that our findings are robust with respect to all the mentioned checks. In the next section, we provide concluding comments and some policy implications of our results.

6. Concluding remarks

The BP aimed at creating a common European Higher Education Area (EHEA) in order to enhance the competitiveness of European HEIs, improve teaching and research activities, and make academic institutions more attractive for students and staff. By looking at this issue from a teaching-efficiency evaluation perspective, the reform would have implied a general average improvement, a process of convergence of universities' performances as well as a substantial reduction of gaps among both universities and geographical areas.

In this study we aimed at testing these hypothesis for a panel of 69 Italian universities by using data from Italian National Evaluation Committee for the period 2000-2010. Initially, we employed a bootstrapped DEA procedure in order to derive efficiency estimates of HEIs. Our results show that, on average, teaching efficiency increased between 2003-2005 and then started to decline. It seems reasonable to attribute the efficiency gain to the introduction of new courses although the identification of a causal relationship is not straightforward in this context. Moreover, it should be noted that a proper evaluation of the impact of the

[26] The results of these estimates are not reported here but are available from authors upon request.

reform on teaching would involve outcomes, *e.g.* the knowledge acquired by students throughout their career.

We then evaluated unconditional β and σ *convergence* in order to assess the convergence of Italian HEIs to the frontier of best practice and we found evidence of a constant process of convergence at university level in the observed period. Finally, we employed a Partial Adjustment Model and compared the persistence of inefficiency at both university and regional level.

Overall, our analysis suggests that the positive effect of BP on Italian universities' teaching efficiency was merely temporary. Moreover, although the implementation of BP resulted in a process of convergence of HEIs performances along the observed period, we find evidence of persistence both in geographical gaps and among universities. From a policy point of view, it calls for more proper policies, designed to deal with this relevant issue for Italian HE system.

Although, our empirical findings appear robust with respect to several checks, we remark that our study focused on a single aspect of universities' activity – that is teaching – and evaluates efficiency by using imperfect quality proxies.

For the abovementioned considerations, developments in this direction would consider the evaluation of research activities as well as a richer and more appropriate set of quality measures. Further analyses should be dedicated to a more exhaustive investigation of convergence by introducing conditional *β-convergence* in order to shed more light on the effect that the BP have had on both regional and geographical heterogeneity.

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TABLES AND FIGURES

Table 1

Descriptive statistics of employed variables

Variables	*mod 1*	*mod 2*	Obs.	Mean	Std. Dev.
			Inputs		
STUD	♦	♦	759	26031.76	24269.33
ENR_9		♦	759	1139.60	1061.54
AS	♦	♦	759	839.96	834.38
STR	♦	♦	759	16968	13684.23
			Outputs		
GRAD	♦	♦	759	3710.98	3565.39
GRAD_R		♦	759	890.75	1155.56

Notes: variables are inputs (STUD – total number of students; ENR_9 – enrollments with high secondary school mark; AS – academic staff; STR – number of available places in teaching rooms, libraries and laboratories) and outputs (GRAD – number of graduates; GRAD_R – number of regular graduates).
Source: our elaboration on data provided by Italian CNVSU.

Table 2

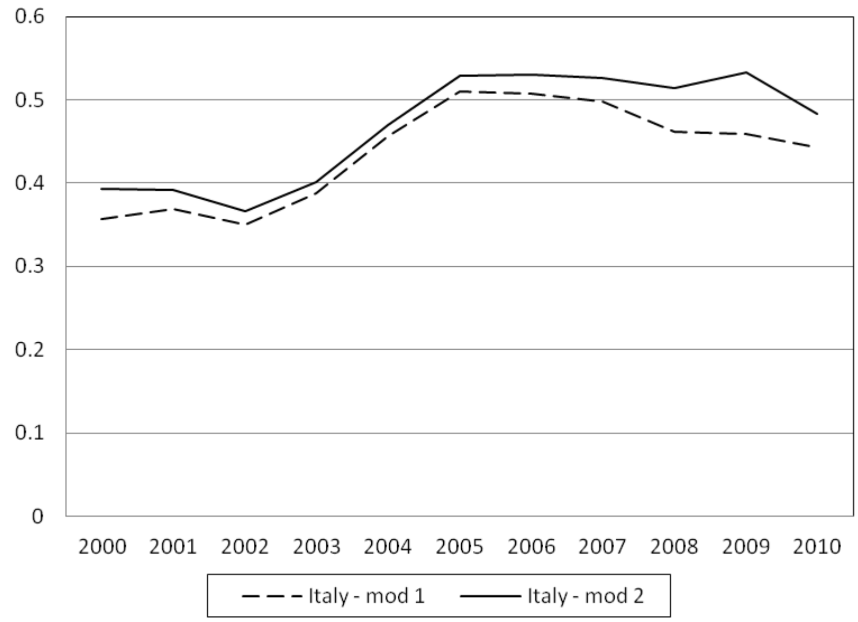
Average efficiency scores estimates by year (pooled data)

Model	Efficiency scores	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	All sample
mod 1	CRS	0.3807	0.3923	0.3756	0.4130	0.4874	0.5423	0.5351	0.5271	0.4896	0.4878	0.4704	**0.4637**
	CRS BIAS CORRECTED	0.3569	0.3684	0.3500	0.3878	0.4566	0.5097	0.5068	0.4984	0.4619	0.4590	0.4432	**0.4362**
	VRS	0.4729	0.4805	0.4463	0.4944	0.5762	0.6421	0.6381	0.6266	0.5952	0.5964	0.5621	**0.5573**
	VRS BIAS CORRECTED	0.3926	0.4114	0.4059	0.4566	0.5300	0.5897	0.5925	0.5795	0.5527	0.5536	0.5200	**0.5077**
mod 2	CRS	0.4161	0.4152	0.3924	0.4279	0.5049	0.5671	0.5683	0.5715	0.5626	0.5802	0.5450	**0.5047**
	CRS BIAS CORRECTED	0.3930	0.3918	0.3667	0.4006	0.4700	0.5296	0.5304	0.5261	0.5147	0.5336	0.4833	**0.4672**
	VRS	0.4916	0.4972	0.4605	0.5081	0.5937	0.6637	0.6702	0.6773	0.6635	0.6933	0.6796	**0.5999**
	VRS BIAS CORRECTED	0.4051	0.4263	0.4144	0.4607	0.5322	0.5920	0.5994	0.5853	0.5644	0.5882	0.5532	**0.5201**

Notes: average by year output oriented efficiency scores estimated on intertemporal frontier. Scores have been estimated by employing Simar and Wilson (1998) consistent bootstrap estimation procedure. Scores are distinguished with respect to model specification (mod 1 and mod 2).
Source: our computation

Figure 1

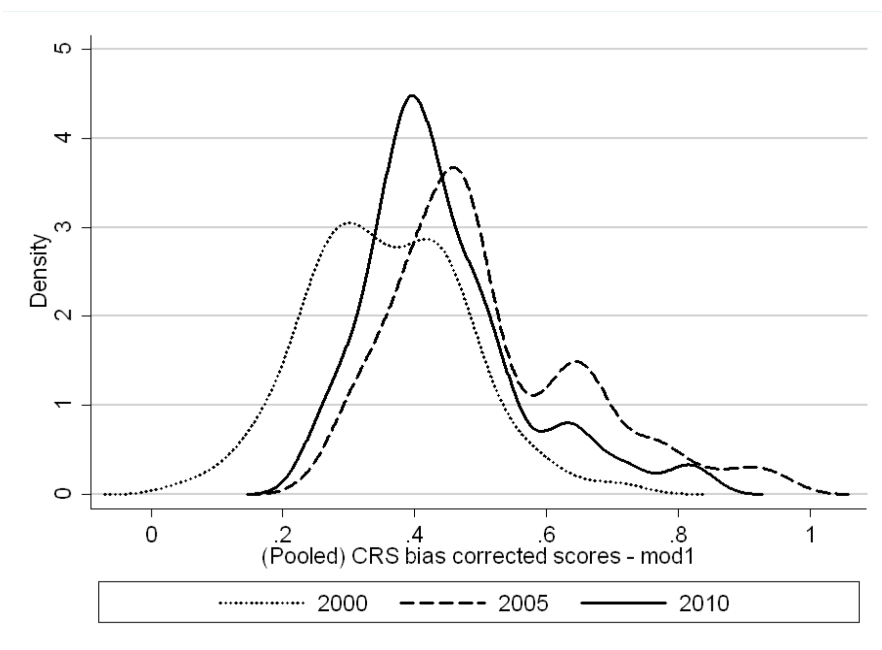
Average CRS bias corrected scores - different specifications (mod 1 and mod 2)



Notes: average by year CRS bias corrected scores estimated on intertemporal frontier, distinguished by model specification.
Source: our computation

Figure 2

Kernel densities estimates of the CRS bias corrected scores distribution



Notes: CRS bias corrected scores estimated on intertemporal frontier. Univariate kernel smoothing distribution (Wand and Jones, 1995), estimated through reflection method. The criterion for bandwidth selection followed the plug-in method proposed by Sheater and Jones (1991). Plots show respectively the first, the turning point and the last year kernel estimates.
Source: our computation.

Table 3

Beta convergence of (Pooled)CRS bias corrected estimates (intertemporal frontier)

Variables	mod 1				mod 2			
	OLS	OLS	FE	SYS-GMM	OLS	OLS	FE	SYS-GMM
$\ln \hat{\theta}_{i,t-1}$	-0.183***	-0.214***	-0.423***	-0.935***	-0.169***	-0.197***	-0.392***	-0.932***
	(0.0242)	(0.0264)	(0.0309)	(0.1130)	(0.0232)	(0.0257)	(0.0278)	(0.0925)
$\Delta\hat{\theta}_{i,t-1}$	--	0.100*	0.137***	0.126**	--	0.068	0.0907**	0.038
	--	(0.0511)	(0.0526)	(0.0556)	--	(0.0505)	(0.0564)	(0.0574)
Constant	-0.137***	-0.164***	-0.345***	-0.787***	-0.115***	-0.134***	-0.292***	-0.724***
	(0.0222)	(0.0236)	(0.0258)	(0.1030)	(0.0194)	(0.0212)	(0.0217)	(0.0794)
HEIs FE	no	no	yes	no	no	no	yes	no
F-test (p-value)	--	--	0.000	--	--	--	0.000	--
Observations	690	621	621	621	690	621	621	621
R^2	0.131	0.160	0.299	--	0.118	0.142	0.275	--

*Notes: robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*
Source: our computation.

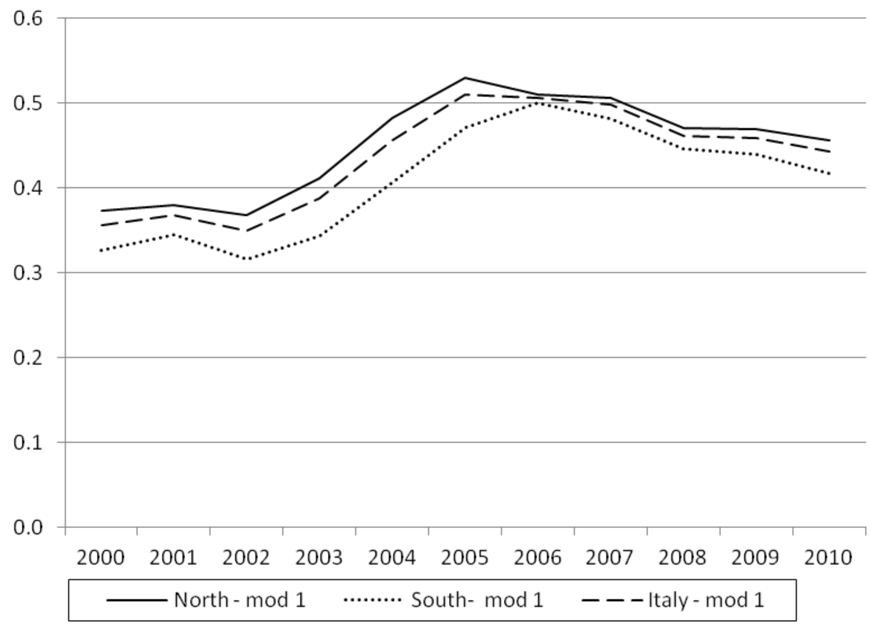
Table 4
Sigma convergence of CRS bias corrected estimates (intertemporal frontier)

Variables	mod 1				mod 2			
	OLS	OLS	FE	SYS-GMM	OLS	OLS	FE	SYS-GMM
$E_{i,t-1}$	-0.172***	-0.188***	-0.496***	-1.061***	-0.163***	-0.175***	-0.472***	-1.036***
	(0.0280)	(0.0309)	(0.0448)	(0.131)	(0.0260)	(0.0296)	(0.0369)	(0.114)
$\Delta E_{i,t-1}$		-0.014	0.057	0.105	--	-0.023	0.018	0.0539
		(0.0559)	(0.0498)	(0.0710)	--	(0.0608)	(0.0549)	(0.0668)
Constant	-0.005	-0.004	-0.018***	-0.061*	-0.005	-0.005	-0.018***	-0.063*
	(0.0059)	(0.0061)	(0.0019)	(0.0325)	(0.00582)	(0.0060)	(0.0017)	(0.0351)
HEIs FE	no	no	yes	no	no	no	yes	no
F-test (p-value)	--	--	0.000	--	--	--	0.000	--
Observations	690	621	621	621	690	621	621	621
R^2	0.115	0.130	0.317	--	0.109	0.119	0.309	--

*Notes: robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*
Source: our computation.

Figure 3

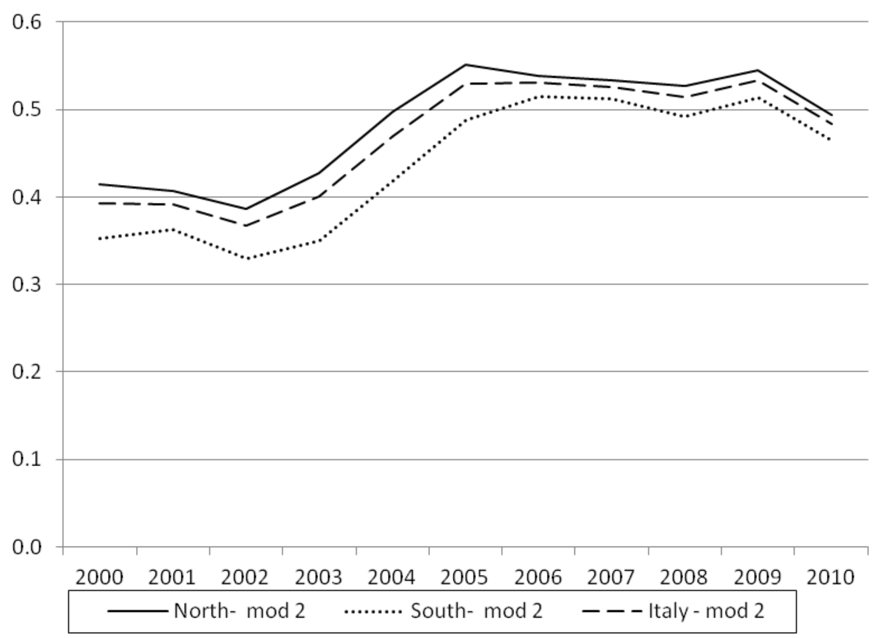
Average CRS bias corrected scores for geographical area in different specifications (mod 1)



Notes: average by year CRS bias corrected scores estimated according to mod 1 on intertemporal frontier, distinguished for geographical area. Source: our computation.

Figure 4

Average CRS bias corrected scores for geographical area in different specifications (mod 2)



Notes: average by year CRS bias corrected scores estimated according to mod 2 on intertemporal frontier distinguished for geographical area. Source: our computation.

Table 5

PAM of CRS bias corrected estimates at both university and regional level (intertemporal frontier)

Variables	University level				Regional level			
	mod 1		***mod 2***		***mod 1***		***mod 2***	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
$\ln \hat{\theta}_{i,t-1}$	0.817***	0.671***	0.831***	0.692***	0.816***	0.710***	0.829***	0.743***
	(0.0242)	(0.0332)	(0.0232)	(0.0327)	(0.0343)	(0.0210)	(0.0351)	(0.0216)
Constant	-0.137***	-0.267***	-0.115***	-0.230***	-0.146***	-0.243***	-0.127***	-0.199***
	(0.0222)	(0.0294)	(0.0194)	(0.0269)	(0.0310)	(0.0194)	(0.0288)	(0.0185)
HEIs FE	no	yes	no	yes	no	yes	no	yes
F-test (p-value)	--	0.006	--	0.002	--	0.169	--	0.240
Observations	690	690	690	690	190	190	190	190
R^2	0.750	0.542	0.763	0.568	0.771	0.634	0.774	0.658

*Notes: robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Equation (4) estimates distinguished by model specification and level. Regional level computed by averaging universities scores.*
Source: our computation

Table 6

Average efficiency scores estimates by year. (Frontiers estimated separately for each year)

Model	Efficiency scores	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	All sample
mod 1	CRS	0.6604	0.6651	0.4734	0.6205	0.5556	0.5694	0.6611	0.5867	0.5867	0.6375	0.6000	**0.6015**
	CRS BIAS CORRECTED	0.5889	0.5956	0.3824	0.5491	0.4778	0.4875	0.5943	0.5038	0.5053	0.5606	0.5196	**0.5241**
	VRS	0.7369	0.7281	0.7044	0.6905	0.6782	0.7025	0.7637	0.7063	0.7063	0.7314	0.7183	**0.7151**
	VRS BIAS CORRECTED	0.6138	0.6060	0.5940	0.5703	0.5490	0.5808	0.6651	0.5858	0.5866	0.6177	0.6077	**0.5979**
mod 2	CRS	0.6966	0.7129	0.5625	0.6900	0.6464	0.6854	0.6717	0.5934	0.5934	0.6791	0.6935	**0.6568**
	CRS BIAS CORRECTED	0.5737	0.5964	0.4177	0.5734	0.5380	0.5645	0.5562	0.4582	0.4575	0.5622	0.5854	**0.5348**
	VRS	0.7671	0.7779	0.7692	0.7336	0.7512	0.7691	0.7839	0.7528	0.7528	0.7624	0.7952	**0.7650**
	VRS BIAS CORRECTED	0.6151	0.6320	0.6352	0.5809	0.6187	0.6296	0.6623	0.6257	0.6259	0.6258	0.6809	**0.6302**

Note: table displays averaged by year output oriented efficiency scores estimated by contemporaneous frontiers. Scores have been estimated by employing Simar and Wilson (1998) consistent bootstrap estimation procedure. Scores are distinguished with respect to model specification (mod 1 and mod 2).
Source: our computation.

Table 7

Beta convergence of CRS bias corrected estimates(Frontiers estimated separately for each year)

Variables	mod 1					mod 2				
	OLS	OLS	FE	FE2	SYS-GMM	OLS	OLS	FE	FE2	SYS-GMM
$\ln\hat{\theta}_{i,t-1}$	-0.486***	-0.411***	-0.912***	-0.666***	-1.402***	-0.656***	-0.575***	-1.099***	-0.963***	-1.389***
	(0.0475)	(0.0565)	(0.0508)	(0.0972)	(0.0816)	(0.131)	(0.0941)	(0.0578)	(0.113)	(0.0484)
$\Delta\hat{\theta}_{i,t-1}$	--	-0.279***	-0.052	-0.0322	0.131***	--	-0.191***	0.064	-0.000443	0.169***
	--	(0.0379)	(0.0382)	(0.0675)	(0.0384)	--	(0.0579)	(0.0407)	(0.0217)	(0.0454)
Constant	-0.346***	-0.303***	-0.655***	-0.474***	-0.987***	-0.445***	-0.399***	-0.763***	-0.550***	-0.959***
	(0.0324)	(0.0400)	(0.0369)	(0.0690)	(0.0699)	(0.0866)	(0.0627)	(0.0422)	(0.0962)	(0.0529)
HEIs FE	no	no	yes	yes	no	no	no	yes	yes	no
F-test (p-value)	--	--	0.000	0.000	--	--	--	0.000	0.000	--
year FE	no	no	no	yes	--	no	no	no	yes	--
F-test (p-value)	--	--	--	0.000	--	--	--	--	0.000	--
Observations	690	621	621	621	621	690	621	621	621	621
R^2	0.264	0.354	0.518	0.738	--	0.338	0.385	0.534	0.636	--

*Notes: robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*

Source: our computation.

Table 8

Sigma convergence of CRS bias corrected estimates (Frontiers estimated separately for each year)

Variables	mod 1					mod 2				
	OLS	OLS	FE	FE2	SYS-GMM	OLS	OLS	FE	FE2	SYS-GMM
$E_{i,t-1}$	-0.292***	-0.270***	-0.663***	-0.666***	-1.168***	-0.569***	-0.473***	-0.962***	-0.963***	-1.227***
	(0.0407)	(0.0477)	(0.0421)	(0.0972)	(0.0948)	(0.164)	(0.110)	(0.0552)	(0.113)	(0.0333)
$\Delta E_{i,t-1}$	--	-0.187***	-0.035	-0.0322	0.090	--	-0.235***	-0.002	-0.000443	0.079***
	--	(0.0426)	(0.0382)	(0.0675)	(0.0595)	--	(0.0877)	(0.0405)	(0.0217)	(0.0239)
Constant	-0.009	-0.007	-0.022***	-0.0159	-0.026	-0.022**	-0.018	-0.039***	-0.0381**	-0.045
	(0.0069)	(0.0072)	(0.0070)	(0.0171)	(0.0356)	(0.0110)	(0.0113)	(0.0118)	(0.0191)	(0.0419)
HEIs FE	no	no	yes	yes	no	no	no	yes	yes	no
F-test (p-value)	--	--	0.000	0.000	--	--	--	0.000	0.000	--
year FE	no	no	no	yes	--	--	--	--	yes	--
F-test (p-value)	--	--	--	0.942	--	--	--	--	0.840	--
Observations	690	621	621	621	621	690	621	621	621	621
R^2	0.169	0.212	0.388	0.394		0.298	0.355	0.500	0.509	--

*Notes: robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*

Source: our computation.

Table 9

PAM of CRS bias corrected estimates at both university and regional level (mod 1 & mod 2 - Frontiers estimated separately for each year) including 'by year' effects

Variables	University level				Regional level			
	mod 1		***mod 2***		***mod 1***		***mod 2***	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
$\ln \hat{\theta}_{i,t-1}$	0.708***	0.410***	0.434***	0.101	0.740***	0.456***	0.653***	0.333***
	(0.0396)	(0.0801)	(0.161)	(0.120)	(0.0551)	(0.0802)	(0.0732)	(0.0455)
Constant	-0.326***	-0.810***	-0.771***	-0.957***	-0.229***	-0.416***	-0.172***	-0.378***
	(0.0263)	(0.0468)	(0.119)	(0.139)	(0.0432)	(0.0635)	(0.0516)	(0.0347)
HEI or Regional FE	no	yes	no	yes	no	yes	no	yes
F-test (p value)	--	0.002	--	0.000	--	0.000	--	0.000
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
F-test (p value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	690	690	690	690	190	190	190	190
R^2	0.633	0.473	0.316	0.228	0.719	0.636	0.649	0.573

*Notes: robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*
Source: our computation.

APPENDIX

Table A.1
Descriptive statistics of employed variables: average values per year

Years	STUD	ENR_9	AS	STR	GRAD	GRAD_R
2000	24254.09	1008.28	751.29	14139.93	2685.30	164.41
2001	24366.67	1160.49	796.06	14344.65	2832.42	178.62
2002	25615.80	1326.42	813.42	15903.09	2910.30	250.94
2003	25000.07	1351.39	825.87	16710.10	3397.04	509.90
2004	25443.90	1342.10	866.75	17285.17	3883.52	747.03
2005	26208.45	1287.78	890.75	17674.43	4346.49	890.13
2006	25910.99	1245.43	889.57	17986.65	4329.74	1090.28
2007	25864.16	1109.75	900.36	18290.39	4276.09	1418.51
2008	29519.07	1062.30	872.16	18339.10	4212.14	1513.74
2009	29317.48	867.28	826.30	18037.68	4172.58	1441.01
2010	24848.65	774.43	807.00	17936.80	3775.13	1593.74
All sample	**26031.76**	**1139.61**	**839.96**	**16968.00**	**3710.98**	**890.75**

Note: descriptive statistics of employed variables by year.
Source: our elaboration on data provided by Italian CNVSU

Table A.2

Average efficiency scores with respect to geographical areas (intertemporal frontier)

Geographical areas	Model	Efficiency scores	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	All sample
Centre-north	*mod 1*	CRS	0.3978	0.4044	0.3960	0.4390	0.5191	0.5677	0.5421	0.5389	0.4999	0.5006	0.4885	0.4813
		CRS BIAS CORRECTED	0.3729	0.3806	0.3676	0.4111	0.4831	0.5300	0.5104	0.5069	0.4703	0.4692	0.4569	0.4508
		VRS	0.5109	0.5092	0.4725	0.5285	0.6143	0.6750	0.6499	0.6417	0.6118	0.6167	0.5874	0.5834
		VRS BIAS CORRECTED	0.4084	0.4237	0.4262	0.4857	0.5609	0.6143	0.5990	0.5896	0.5659	0.5696	0.5393	0.5257
	mod 2	CRS	0.4396	0.4310	0.4149	0.4566	0.5369	0.5921	0.5794	0.5862	0.5837	0.6014	0.5709	0.5266
		CRS BIAS CORRECTED	0.4145	0.4073	0.3866	0.4273	0.4978	0.5516	0.5386	0.5336	0.5267	0.5445	0.4932	0.4838
		VRS	0.5333	0.5308	0.4904	0.5459	0.6367	0.7011	0.6917	0.7072	0.6997	0.7343	0.7341	0.6368
		VRS BIAS CORRECTED	0.4230	0.4433	0.4361	0.4902	0.5638	0.6175	0.6097	0.5993	0.5793	0.6061	0.5737	0.5402
South and islands	*mod 1*	CRS	0.3488	0.3696	0.3373	0.3642	0.4279	0.4948	0.5221	0.5049	0.4703	0.4637	0.4364	0.4309
		CRS BIAS CORRECTED	0.3269	0.3456	0.3168	0.3440	0.4069	0.4717	0.5001	0.4826	0.4462	0.4398	0.4173	0.4089
		VRS	0.4017	0.4266	0.3972	0.4306	0.5048	0.5806	0.6159	0.5983	0.5639	0.5584	0.5146	0.5084
		VRS BIAS CORRECTED	0.3629	0.3884	0.3677	0.4020	0.4721	0.5435	0.5802	0.5607	0.5281	0.5238	0.4837	0.4739
	mod 2	CRS	0.3721	0.3855	0.3502	0.3742	0.4450	0.5201	0.5475	0.5440	0.5232	0.5406	0.4964	0.4635
		CRS BIAS CORRECTED	0.3527	0.3626	0.3292	0.3505	0.4179	0.4883	0.5150	0.5121	0.4922	0.5132	0.4647	0.4362
		VRS	0.4133	0.4342	0.4044	0.4372	0.5130	0.5936	0.6299	0.6214	0.5954	0.6165	0.5774	0.5306
		VRS BIAS CORRECTED	0.3715	0.3945	0.3737	0.4054	0.4728	0.5443	0.5802	0.5590	0.5364	0.5548	0.5147	0.4825

Note: Average by year output oriented efficiency scores estimated by intertemporal frontier. Scores have been estimate by employing Simar and Wilson (1998) consistent bootstrap estimation procedure. Scores are distinguished with respect to model specification (mod 1 and mod 2).

Source: our computation

Table A.3
Panel data model selection test results

MODEL	LEVEL	EQUATION	FE vs OLS	FE vs RE
mod1	university level	BETA	FE	FE
		SIGMA	FE	FE
		PAM	FE	FE
	regional level	BETA	FE	FE
		SIGMA	FE	FE
		PAM	OLS	FE
mod2	university level	BETA	FE	FE
		SIGMA	FE	FE
		PAM	FE	FE
	regional level	BETA	FE	FE
		SIGMA	FE	FE
		PAM	OLS	FE

Note: this table displays model selection test results with respect to CRS bias corrected scores estimated by intertemporal frontier. FE stands for HEIs FE; FE vs. OLS test performed by F-test; FE vs. RE test performed by Hausman specification test.
Source: our computation