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Does the Extent of Per-Case Payment System Affect Hospital Efficiency? Evidence from the Italian NHS

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Abstract

Recently increasing public pressure to contain costs in the healthcare sector has led many national governments to introduce some type of prospective payment system and reduce the scope of global budgeting. This study investigates the extent to which the reimbursement systems of the Italian hospital sector have an impact on hospitals' technical efficiency. Because of high variation in the financing and provision of healthcare services among regions and hospitals, Italy represents an interesting case study to test these effects. A two-stage Data Envelopment Analysis was employed, in which the efficiency scores of all Italian hospitals were first calculated and then regressed on different environmental variables to capture the role of reimbursement systems. The results found a significant impact of the use of Diagnostic-Related Group-based prospective payment systems on hospitals' efficiency.

Keywords: Hospital efficiency, Data Envelopment Analysis, prospective payment systems, hospital ownership type

JEL: C14; I11; I18

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1. Introduction

Public pressure to contain costs in the healthcare sector has increased in all of the Organisation for Economic Co-operation and Development (OECD) countries during the past few years, leading many national governments to strive for new approaches to reach this important goal. This study investigates the effects of payment systems on hospitals' technical efficiency using Italy as a case study. The Italian National Health Service (NHS) is a particularly interesting case because it has been subject to a significant decentralization process over time, in which healthcare responsibilities have been progressively devolved to regional governments.

Beginning in the 1990s, the need to curb spending to meet the Maastricht criteria led to a set of reforms with the threefold goal of introducing efficiency into the healthcare system, creating an internal market for healthcare services, and increasing the autonomy of regions regarding the financing and delivery of healthcare. As a result, within the Italian national regulatory framework, regions are free to administer, organize, and finance healthcare in accord with their populations' needs. Therefore, marked regional differences exist in the adopted models, particularly regarding the extent to which the Diagnosis Related Group (DRG) system is employed for the coverage of overall financing of hospital care.

In this study, we contribute to the existing empirical literature by providing an econometric analysis of the relationship between the DRG-based reimbursement systems used by the Italian regions and the performance of the hospital system. First, to estimate the technical efficiency of the Italian hospital sector, we apply Data Envelopment Analysis (DEA) to a large panel of Italian hospitals from 1999 through 2010. Then, we investigate the impact of environmental variables (or non-discretionary inputs) on hospital technical efficiency, focusing on the role played by different payment systems, by performing a regression analysis using efficiency scores as the dependent variable and the environmental variables as predictors.

Regarding the effects of payment systems, our analysis found a significant impact of DRG-based prospective payment systems (PPSs) on hospital efficiency. In particular, we found evidence that hospitals financed by PPS tended on average to be more efficient than those financed by a global budget. This difference appears particularly marked for public hospitals, where hospital trusts (financed by DRG tariffs) are clearly more efficient than hospital units, which are financed by global budgets.

The remainder of the paper is organized as follows. In the next two sections we provide the conceptual framework and a discussion of Italy's institutional background, respectively, followed by a review of the relevant literature on the relationship between payment systems and hospitals' efficiency. Then, we discuss some of the core methods of measuring technical efficiency, describe the data and outline the empirical strategy, before reporting and commenting the results. The final section offers some concluding remarks.

2. Conceptual Framework

The payment system, with its associated incentives provided to economic actors, is widely recognized as a relevant factor for explaining the performance of the hospital sector. As has been discussed by a broad and established stream of research literature (Ellis and McGuire 1986; Ma 1994), hospital payment schemes based on full reimbursement of the incurred costs do not effectively incentivize cost containment, which leads to a "medical arms race" among hospitals and, thus, to an escalation of healthcare costs (Street et al. 2011). The considerable increases in healthcare expenditures over time have stimulated several OECD countries to reform their provider payment systems (Busse et al. 2011) to provide more effective incentives to achieve cost containment. For example, in the US, a DRG-based PPS was introduced in 1983 to pay hospitals for each episode of care provided to Medicare patients. Under that payment system, hospitals were reimbursed a fixed tariff for each patient treated, based on the DRG classifications. Following the US experience, many European countries have implemented some type of prospective payments for hospital care, thus reducing the scope of retrospective reimbursements.

The introduction of PPS intends to alter the incentives for hospitals to contain costs. Generally, the adoption of PPS is associated with a variety of typical hospital incentives (Busse et al. 2011), some, but not all, of which are desirable. First, hospitals that are paid by a fixed-price are expected to reduce the average length of stay to the point where shorter stays reduce inpatient costs and increase profit margins. PPS are also likely to encourage hospitals to reduce unnecessary medical procedures for each patient treated. Along with incentives to minimize costs per case, hospitals under PPS can attempt to increase their revenues by increasing admissions (to the extent that this is possible)[1].

As highlighted by Ellis and Miller (2008), the overall PPS effect on cost containment, although always ambiguous, ultimately depends on the accuracy of the payment scheme. Thus, a highly diversified scheme that minimizes cost variation within each payment category may induce hospitals to "game" the system by classifying patients into higher payment categories (referred to as "upcoding" or "DRG creep"). However, that scheme also decreases incentives for hospitals to cream skim patients, by selecting the more lucrative cases. The situation is reversed for the less diversified and accurate payment scheme.

The expected incentives for hospitals to save on costs under PPS have caused many concerns about possible reductions in the quality of care, although the current evidence in the literature suggests that introducing PPS does not significantly deteriorate quality (Coulam and Gaumer 1991; Cavalieri, Gitto and Guccio 2013; Cappellari, Paoli and Turati 2014).

Many contextual factors could matter to the realization of the expected incentives provided by PPS, among which hospital ownership appears to be particularly relevant. A sizable body of literature (*e.g*. Alchian and Demsetz 1972; Brekke, Siciliani and Straume 2015) has emphasized that hospitals' objective function ultimately determines their incentives to cost containment. Moreover, there is a growing stream of empirical

[1] According to Langenbrunner, Cashin, and O'Dougherty (2009), because providers usually have more control over resource use per case than they have over the total number of admissions, the incentive to restrain costs is typically stronger.

research investigating the ways that hospital ownership type affects treatment as well as patient choices. Some of these studies find a significant difference among hospital types, while others find little difference (Duggan 2000; Sloan et al. 2001; Horwitz and Nichols 2009; Bayindir 2012).

Thus, the objective function of private for-profit hospital organizations, of which the owner is the residual claimant, should offer effective incentives to control costs. On the other hand, public and private not-for-profit hospital organizations, which are characterized by the presence of a non-distributional constraint, should have lower incentives to reduce costs. Furthermore, even if they shared the same non-distributional constraint, public and private not-for-profit hospitals could differ because only the latter have effective incentives to comply with hard budget constraints, while the former tend to operate under soft budget constraints (Kornai 2009; Shen and Eggleston 2009). Moreover, in the presence of recurring governmental bailouts, the incentives to cost containment provided by PPS could be significantly weakened.

In the Italian case, hospital type has a central role (Barbetta, Turati and Zago 2007) because there are many different organizations that can be characterized as public, private for-profit, or private not-for-profit hospitals. Moreover, the mixture is not uniform across the country and there is significant heterogeneity in the distribution of hospitals across Italian regions. Therefore, this analysis explicitly accounts for the characteristics of hospitals when determining the effects of the payment system on hospital performance.

3. Background

3.1 Hospital Care in Italy

The Italian NHS was established in 1978 to provide universal access to a uniform level of care throughout the country, financed by general taxation. The system is organized as a multi-tier structure. The national level (Ministry of Health) has exclusive power over national health planning, including setting overall goals, annual financial resources for healthcare, and regarding the definition of the *Livelli Essenziali di Assistenza* (Essential Levels of Care [LEA]) that must be uniformly guaranteed across the country. The nineteen regions and two autonomous provinces have the constitutional mandate to organize and deliver healthcare through a network of geographic- and population-defined *Aziende Sanitarie Locali* (Local Health Authorities [ASLs]) and public and accredited private healthcare providers.

Beginning in the early 1990s, Italy undertook a set of reforms that fundamentally shaped the organization, method of financing healthcare, and allocation of resources among the different tiers of government (France, Taroni and Donatini 2005). The reform process was inspired by the principles of regionalization, managed competition, and managerialism. Regionalization implied a significant transfer of healthcare powers from the state to the regions, which are now responsible for funding their healthcare expenditures with regional taxes[2] and user fees (despite the national equalization mechanism that compensates cross-sectional differences in regional fiscal capacities). Regions have full discretion for deciding how to organize their healthcare systems, particularly regarding the choice to provide, and autonomously finance, healthcare services beyond the mandatory standard benefit package (*i.e.* LEA) and whether to retain the purchasing role or transfer it to the local health authorities (LHAs)

The separation of purchasing from providing functions has been endorsed as a part of the quasi-market model introduced into the public health sector to boost competition and, thereby, increase efficiency (Turati 2013). The creation of an internal market has called for a managerial reorganization of the former *Unità Sanitarie Locali* (Local Health Units), which were transformed into independent public entities (*i.e.* ASLs) with their own budgets and management. ASLs were asked to hive-off major public hospitals, which were granted the status of trusts, *Aziende Ospedaliere* (hospital trusts [AO]), with full managerial autonomy. Thus, hospital providers in Italy's public healthcare system

[2] In 1997, the previous sickness contributions were substituted by both a new *Imposta Regionale sulle Attività Produttive* (Regional Tax on Productive Activities) and an *Addizionale IRPEF* (Surcharge on Personal Income Tax).

range from public hospital units directly run by LHAs (*Ospedali a Gestione Diretta* or *Presidi Ospedalieri* [HUs]), public hospital trusts formally independent of LHAs (*i.e.* AO), and accredited private hospitals (either for-profit or not-for-profit) that compete with the public hospitals in the delivery of services.

To make the pro-competitive reform effective, a new financing system for hospital services was defined. Regarding inpatient care[3], the system is grounded on two components. First, there are per case tariffs related to the DRG classification of discharges (version 24 since 2009). Second, lump-sum transfers are used to finance provision of those services (*e.g.* integrated care, preventive services, emergency treatment, experimental programs, and transplants) for which "tariffs are deemed inadequate or inappropriate" (Fattore and Torbica 2006, 252). [4] The fixed-price component applies to both public and accredited private hospitals and has replaced the previous financing systems based on full retrospective payments and per-day fees, respectively. The sole exceptions are public hospitals directly run by LHAs (*i.e.* HUs), whose activities continue to be financed retrospectively through the LHA budget.[5]

With the Decree of December 14, 1994 n. 169, the Italian Ministry of Health laid down the first list of national tariffs, based on cost data collected from eight hospitals located in Italy's northern and central regions (Taroni 1996).[6] Consistently with the logic of regionalization, regional governments were allowed either to opt for the national DRG rates or to establish their own DRG tariffs to make them closer to their actual costs

[3] Outpatient care is paid on a fee-for-service basis.
[4] The reasons for the inappropriateness of tariff financing for these services are different. Services, such as organ transplants, have a regional interest, require sophisticated technologies, and need to be concentrated in one or just a few hospitals. Other services, such as the ones related to emergency treatment, require an amount of resources that is independent of demand. Finally, there are peculiarities to some hospitals (such as teaching hospitals) that are difficult to deal with using the tariff mechanism (Morandi 2009). Ideally, lump-sum transfers should be determined according to the efficient cost of their provision. Regions have full autonomy over the identification of the services to include and, thus, may alter the composition of hospital funding, which reduces the scope of activity-based payments.
[5] According to Morandi et al. (2008), HUs are "… *de facto* financed on the basis of the consumption of production factors (personnel, goods and services, etc.)."
[6] Since then, national tariffs have been updated many times, specifically in 1997 (Decree of the Ministry of Health, June 30, 1997), in 2006 (Decree of the Ministry of Health, September 12, 2006), and, recently, in 2012 (Decree of the Ministry of Health, October 18, 2012).

and local specificities.[7] Whichever route was taken, the new financing system had to begin between 1995 and 1997.

While staying within the general criteria set by the national legislation, regional governments have used their regulatory powers with a great deal of autonomy (*e.g.* Jommi, Cantù and Anessi Pessina 2001; Anessi Pessina, Cantù and Jommi 2004; France and Taroni 2005). As a result, organization of healthcare at the regional level is extremely variable, which ultimately results in a different scope of competition in the NHS. Regarding hospital care, regions have chosen the managerial structure of hospitals (*i.e.* either run by LHAs or fully autonomous in management) as well as the extent to which private hospitals are involved in the provision of services, through their accreditation policy. Therefore, the regional institutional options have ranged from the *modello integrato* (integrated model) of Veneto, in which most hospitals are part of LHAs and competition is reduced to a minimum (in other words, accredited private providers play a residual part), to the *modello separato* (separated model) of Lombardy, in which none of the hospitals are run by LHAs and patients are free to select their providers (public or accredited private) (Boni 2007). Nevertheless, since 2002, Lombardy has gradually and deliberately relinquished competition in order to control healthcare expenditure (Brenna 2011).[8]

Regarding the financing of hospital care, regional governments can autonomously identify the specific services to be reimbursed by lump-sum payments within the broad category of facilities described above. The related options influence the relative weight of the forfeit and activity-based components in the overall financing of hospital care and, hence, the strength of the incentives that result from the tariffs.

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[7] Specifically, by choosing their own tariff fees, regions can (Decree of the Ministry of Health, June 30, 1997 n. 178): (1) adopt the national tariffs, eventually modifying them (in excess or defect) on the basis of a predetermined percentage or according to regional policies and needs; (2) define regional tariffs, maintaining the relative weights set at the national level and changing just the DRG's point value; and (3) determine a system of new regional relative weights based on the analysis of actual hospital costs in their territories.

[8] The Lombardy region shifts from a quasi-market to a "quasi-administered" (budget-based) system following the adoption by the central government of a more centralized approach in healthcare, as defined in legislative decree 229/1999 (Cappellari, Paoli and Turati 2014).

With regard to the way tariffs are determined, many regions have adopted their own set of tariffs, using them as incentive tools to pursue specific policy goals rather than tailoring them to meet the efficient costs of providing hospital care (Di Loreto and Spolaore 2004). In this respect, regional tariffs have often been differentiated by type of provider, reflecting the fact that production costs and responses to price incentives are not homogeneous, but vary according to numerous characteristics, such as ownership, volume of activity, hospital functions, and case-mix. In particular, according to Morandi et al. (2008), tariffs represent the real price only for the accredited private hospitals, whereas, for the independent public ones (*i.e.* hospital trusts), tariffs are used as regional devices to assess hospital activities and determine hospital budgets. Finally, to limit providers' tendencies to increase their volumes of services under activity-based payments, some regions (*e.g.* Lombardy) have set caps, ceilings, or targets at the regional, LHA, or hospital level, whereas others (*e.g.* Tuscany) control volumes of production with bilateral contracts (between LHAs and hospitals).

3.2 Previous Literature

The empirical literature on hospital efficiency comprises a huge body of research with numerous scopes, methodologies, and results (Hollingsworth et al. 1999; Hollingsworth 2003, 2012). For this study, attention is restricted to the stream of research that explicitly considered the impact of financing systems, particularly PPS, on hospital efficiency.

Despite the preceding theoretical arguments for cost reductions and efficiency gains under a PPS, empirical evidence is rare and, overall, mixed. In the US, Borden (1988) found no significant technical efficiency gains for ninety-three New Jersey hospitals between 1979 and 1984. Chern and Wan (2000) found similar results in a study of the catch-up effect of technically inefficient hospitals in Virginia (US) over a ten-year period (1984 to 1993). On the contrary, efficiency gains were found by Morey and Dittman (1996), who analyzed the technical inefficiency of 105 hospitals in North Carolina (US). Recently, Rosko and Mutter (2010) compared 543 small US hospitals in rural areas subject to different payment systems. Among other results, they found that the average estimated cost inefficiency was greater in the cost-reimbursed hospitals (15.9 percent) than in the PPS hospitals (10.3 percent), concluding that PPS had a positive impact on efficiency.

Findings from European countries also are mixed. Whereas a positive effect of PPS introduction on technical efficiency was found in Portugal (Dismuke and Sena 1999, 2001), Sweden (Gerdtham et al. 1999a, 1999b), Finland (Linna 2000), Norway (Biorn et al. 2003, 2010; Hagen, Veenstra and Stavem 2006), and Switzerland (Widmer 2011), no efficiency gains were observed in Austria (Sommersguter-Reichman 2000) or Germany (Herwartz and Strumann 2014). A recent study by Meyer (2015) analyzed a panel of 121 public hospitals in Switzerland subject to one of four payment schemes (per diem payments, two flat-rate schemes, and a mixed system) between 2004 and 2009. By isolating the cost-efficiency effects of the different payment schemes, the author found that, compared to per diem, hospitals that are reimbursed by flat payments perform better in terms of cost efficiency. Moreover, the results suggested that hybrid payment schemes create incentives for cost containment, although less than pure ones.

Numerous factors could contribute to explaining the above mixed results. In particular, country-level differences in pre-existing hospital payment systems, and the ways that DRG-based systems are implemented and operated, may contribute to the variation in studies' results. Street et al. (2011) pointed out that, in countries where global budgets preceded DRG-based payments (*e.g.* Sweden, Portugal, and Norway), hospitals' technical efficiency tended to improve, whereas in countries in which a retrospective (*e.g.* US) or per-diem (*e.g.* Austria) payment system was replaced, no significant efficiency gains were experienced as a result of the introduction of PPS. However, the authors posited that these attributions are not definitive because they are deeply influenced by the countries' actual realizations of the payment system (*e.g.* the presence of ceiling or other restrictions) or by the simultaneous introduction of other healthcare reforms (as found by Gerdtham et al. 1999a, 1999b). All these factors may confound the studied relationships and challenge the ability to isolate the relevant effects.

Problems preventing consistency among the studies' results include study-specific methodological shortcomings that may explain the relatively weak evidence. It is noteworthy that most of the above-cited country-level studies employed longitudinal data. Generally, a time-series of four or five years was analyzed, but that may be a too short of a time horizon to detect a relevant effect. On the other hand, when time horizons are excessively long, analysis runs the concrete risk that the observed effect of PPS is driven by unobserved exogenous shocks that occurred during the implementation of the reform (such as other aspects of healthcare reform, advances in medical technology, inflation, and so on). Furthermore, all these studies lack statistical controls for observable characteristics that are strictly related to the hospitals' productive structure, such as ownership.

As for Italy, few studies have analyzed the effects of financing systems on hospital technical efficiency. Among the most relevant ones, Barbetta, Turati, and Zago (2007) investigated the technical efficiency of a balanced panel of 531 Italian hospitals between 1995 and 2000 when the DRG-based payment system was introduced to the hospital sector. The authors estimated an output distant function with parametric (*e.g.* Corrected Ordinary Least Squares and Stochastic Frontiers) and non-parametric (*e.g.* DEA or Free Disposal Hull) approaches to explore the relationships among ownership structure, payment system, and hospital performance. They found a convergence of mean efficiency scores between not-for-profit and public hospitals that supported the general hypothesis that these two types of providers differ in their responses to the introduction of the new payment system, with the former responding more promptly than the latter to PPS implementation. They concluded that these findings suggest that differences in economic performances between competing ownership types are more the result of the institutional settings in which they operate (including payment schemes) than an effect of the incentive structures embedded in the different proprietary types. Contrary to expectations, they further observed a decrease in technical efficiency, more marked for private not-for-profit hospitals than for public hospitals, probably due to public policies intending to reshape the hospital industry and reduce hospitalization rates.

Using a population-based dataset of all operating hospitals in the Lombardy region between 1998 and 2007, Berta et al. (2010) analyzed the ways that three typical distortions induced by the PPS (*i.e.* upcoding, cream skimming and readmissions) influenced Italian hospitals' production function. They found that upcoding and cream skimming negatively affected hospitals' technical efficiency, whereas readmissions had a positive effect. Examining the differences in hospitals' ownership structures, private hospitals appear to be particularly engaged in cream skimming, not-for-profit hospitals have the most readmissions, and no statistically significant differences exist for upcoding among the hospital types. The authors concluded that not-for-profit and public hospitals had similar technical efficiency levels and were more efficient than private hospitals at the beginning of the observation period.

Recently, De Nicola et al. (2014) employed a two-stage bootstrapped DEA analysis to investigate the ways that healthcare organization models, reimbursement systems, and patient flows influenced the efficiency of the Italian regions' healthcare services during 2004–2005. Because the decision-making unit (DMU) is the province (their final sample comprised a balanced panel of 101 provinces), hospital inputs (physicians, nurses, and number of beds) and outputs (total number of patients and case-mix index) were aggregated at the provincial level. Their results found that, among the organizational systems adopted by the Italian regions, the one implemented by Lombardy based on the separation between providers and purchasers evidenced the best results in terms of efficiency. Regarding the hospital reimbursement systems, the regions in which the average costs to deliver healthcare account for the regional characteristics of the population and healthcare structures are likely to improve their performances. Last, patient mobility significantly influenced healthcare efficiency.

This study builds on this literature by explicitly investigating the ways that the different DRG-based payment schemes adopted by Italian regions affect hospital technical efficiency and, furthermore, whether responses vary by hospital type. Compared to the study by Barbetta, Turati, and Zago (2007), this analysis advances our understanding in several important ways. First, it covers a much longer period (twelve versus six years), which arguably is a more appropriate time horizon to capture the effects of the introduction of PPS. Second, in the estimates of hospital efficiency, it adjusts the outputs to account for the cross-sectional and time series variations of case-mix. Third, to model the effect of PPS introduction, we use a continuous indicator (along with a dummy variable) to account for the different extents to which activity-based payment systems are used in each of the regional hospital sectors.

4. Methods, Data, and Empirical Strategy

4.1 Methodological Framework

In this study we focus on the technical efficiency of Italian hospitals using DEA, which involves the comparison of the actual performance of each hospital (here assumed as a Decision Making Unit – DMU) with the optimal performance of the hospitals located on the relevant frontier (or best practice frontier). The aim of this approach is the measurement of technical efficiency by defining a frontier envelopment surface for all sample observations, using linear programming techniques (namely, DEA). DEA is a well-established and useful technique for measuring efficiency in public sector activities and, in particular, in hospital sector.[9] The DEA methodology calculates an efficiency frontier for a set of hospitals, as well as the distance to the frontier for each unit. This distance (efficiency score) between the observed hospital and the most efficient DMU provides a measure of the radial reduction in inputs that could be achieved for a given

[9] Sherman (1984) used DEA for the first time in the hospital sector to measure the efficiency of US teaching hospitals. Thereafter, DEA techniques have been applied also to other health providers, as physicians (Chilingerian and Sherman 1990) and nursing homes (Chattopadhyay and Ray 1996). In particular, DEA hospital studies have spread considerably during '90 in the US, followed by European countries in the subsequent years. Consequently, many DEA applications started to appear also from countries other than the US, such as Canada (Ouellette and Vierstraete 2004) and Turkey (Sahin and Ozcan 2000). Even recently, DEA turns out to be the main technique used in hospital efficiency studies (Hagen, Veenstr and Stavem 2006; Barbetta, Turati and Zago 2007; Mutter, Valdmanis and Rosko 2010; Hadad, Hadad and Simon-Tuval 2013). For a quite comprehensive survey on DEA-based hospital efficiency studies, where also the general findings of the literature are reported, see among the others O'Neill et al. 2008.

measure of output. To describe this point[10], consider n DMUs to be evaluated, a DEA input-oriented efficiency score θ_i is calculated for each hospital solving the following program, for $i=1,\ldots., n,$ in the case of constant returns to scale (CRS):

$$\begin{aligned} &\mathrm{Min}_{\lambda,\theta_i} \quad \theta_i \\ &\text{subject to } Y\lambda - y_i \geq 0 \\ &\qquad\qquad \theta_i x_i - X\lambda \geq 0 \\ &\qquad\qquad \lambda \geq 0 \end{aligned} \qquad [1]$$

where x_i and y_i are respectively the input and output of *i-th* DMU; X is the matrix of input data and Y is the matrix of output data of the sample, λ is a $n\times1$ vector of variables. Solving [1], hospitals with an efficiency score equal to one are located on the frontier and, therefore, their inputs cannot be further reduced without a corresponding decrease in outputs.[11] The model [1] can be modified 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). Furthermore, since traditional DEA statistical estimators of the frontier are obtained from finite samples, the corresponding measures of efficiency are sensitive to the sampling variations of the obtained frontier (Pedraja-Chaparro et al. 1999). Therefore, 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.[12]

The rationale behind bootstrapping is to mimic a true sampling distribution by simulating its Data Generating Process (DGP), which in this paper are the outputs from DEA estimates (Simar and Wilson 2008). Specifically, the procedure relies on

[10] For further details see Fried et al. (2008).

[11] Following the majority of studies on hospital efficiency, in the first stage of our analysis, we consider an input-oriented model, which assumes to minimize the utilization of inputs for the given level of output.

[12] However, some major issues remain unresolved regarding the use of asymptotic results and bootstrap; first, the high sensitivity of non-parametric approaches to extreme value and outliers and, second, the way to allow stochastic noises in a non-parametric frontiers (Simar and Wilson 2008). Other common problems are the dimensionality space (*i.e.* number of input and output variables included in the efficiency analysis) and the reliability of the results obtained by the DEA model; Kneip et al. (1998) refer to this problem in the case of non-parametric estimators as the "curse of dimensionality".

constructing a pseudo-data set and re-estimating the DEA model with this new data set. Repeating the process many times allows to achieve a good approximation of the true distribution of the sampling. The Simar and Wilson (1998) bootstrap procedure estimates bias and the variance of the estimator, which in turn allow to determine confidence intervals. Later, Simar and Wilson (2000) provide an improved and more flexible procedure that automatically corrects for bias without explicit use of a noisy bias estimator.[13] Thus, we employ the latter bootstrapping algorithm (Simar and Wilson 2000) to control for consistency among the efficiency estimates.

Three major approaches have been proposed by the relevant literature to explain efficiency differentials by including environmental variables in the model: the one-stage approach, the two-stage approach (including the semi-parametric bootstrap-based approach) and the conditional nonparametric approach (Simar and Wilson 2008). In the two-stage approach, the nonparametric efficiency estimates obtained in a first stage are regressed in a second stage on covariates interpreted as environmental variables. In this paper we apply the two-stage semi-parametric bootstrap-based approach proposed by Simar and Wilson (2007). More specifically in the second stage of our analysis, we consider the impact of environmental variables (or non-discretionary inputs) on hospital technical efficiency, focusing on the role played by reimbursement systems. Specifically, we assume that the efficiency scores can be regressed – in a cross-section framework – on a vector of environmental variables along the following general specification:

$$\theta_i = f(z_i) + \varepsilon_i \qquad [2]$$

where θ_i represent the efficient scores resulting from the previous stage, z_i is a set of possible non-discretionary inputs and ε_i is a vector of error terms. In the next sections, we will discuss in depth our explanatory variables z_i , as well as some other control variables, which are used to assess the impact of different reimbursement rules on hospital efficiency.

[13] See Simar and Wilson (2008) for the technical details on bootstrap procedures.

Simar and Wilson (2007) underlined that traditional estimators yield to biased estimates due to serial correlation of efficiency scores and suggest to apply semi-parametric two-stage techniques.[14] Since this suggestion, there has been a wide debate on the best method to apply the second-stage DEA analysis; criticism and alternative proposals are based on different assumptions for the DEA-score DGP and sample variation (*e.g.* Hoff 2007; Banker and Natarajan 2008; Ramalho et al. 2010). Recently, Simar and Wilson (2011) showed that the two-step bias-corrected semi-parametric estimator proposed by Simar and Wilson (2007) is the only known method that ensures a feasible and consistent inference on the second stage regression.[15]

4.2 Data Description

All of the data used in this analysis were provided by the Italian Ministry of Health (specifically, the Department of Healthcare) and refer to all Italian hospitals working on behalf of the NHS. Data were examined for errors, outliers, and missing values. The final sample was an unbalanced panel of 11,393 observations over the twelve-year period between 1999 and 2010. For each year, hospital observations ranged from a minimum of 885 to a maximum of 1,044, depending on the year. As a robustness check of our findings, we also analyzed a balanced subsample of 492 hospitals over the twelve years, comprising 5,904 observations.

Table 1 shows the composition of the unbalanced and the balanced panel samples by type of hospital. The two samples include all of the types of hospitals working on behalf of the Italian NHS. Although the unbalanced panel is almost twice the size of the balanced one (11,393 versus 5,904 observations), differences in composition between

[14] More specifically, estimating [2] with Tobit or OLS regressions leads to the violation of the assumption of the independence between ε_i and z_i.

[15] However also this approach shows two weaknesses: first, the potential impact of the environmental factors on the distribution of the efficiency scores occurs only if the separability condition is verified (*i.e.* environmental factors do not influence the shape of the production set). Second, the two-stage approach imposes parametric assumptions on the functional form of the regression and error distribution (Bădin et al. 2013). However, in our case it seems reasonable to assume that the employed environmental factors affect the production process but not the attainable set and its frontier.

the two samples are not very substantial.[16] For both samples, the majority of hospitals (47 percent in the unbalanced and 44 percent in the balanced sample) are public hospitals directly managed by LHAs (*Ospedali a Gestione Diretta* or *Presidi Ospedalieri* [hospital units]); followed by *Case di Cura Accreditate* (accredited private for-profit hospitals) at 35 percent and 37 percent, respectively; *Aziende Ospedaliere* (hospital trusts) at 9 percent and 7 percent, respectively; and, finally, by not-for-profit hospitals[17], at 9 percent and 11 percent, respectively. Thus, in the following analysis, we employ the full unbalanced panel data sample, and we provide and report some robustness checks of our findings using the balanced subsample.

(Insert TABLE 1 about here)

Our dataset includes information on different inputs and outputs usually considered in the literature on hospital efficiency. Among the input variables, we include the number of beds as a proxy measure of capital and the number of personnel units (physicians, nurses, and others). Similarly, output variables are measures of the number of inpatient days, the number of discharged patients and the number of case-mix adjusted discharged patients. Unfortunately, other variables related to the production process (*e.g.* day hospital beds, outpatient's departments and so on) or to the hospitals' outcomes (*e.g.* discharge mortality, readmission rates, and so on) [18] were not available for the analysis.[19]

(Insert TABLE 2 about here)

(Insert TABLE 3 about here)

[16] The existing differences are due to several reasons such as missing information for some years, mergers or closure, changes in hospital's denomination, errors in hospital codes and so on.
[17] Following the same classification as Barbetta, Turati and Zago (2007), we grouped in this category teaching and research hospitals incorporated as both public and private bodies (*Istituti di Ricovero e Cura a Carattere Scientifico, pubblici e privati*), university hospitals (*Policlinici Universitari*) and hospitals run by religious bodies (*Ospedali Classificati*).
[18] These data were not available for the entire study period; hence, we were able to collect only very partial information that could not be exploited in our estimations.
[19] Furthermore, data limitations preclude the opportunity to incorporate hospital costs (such as staff costs, capital costs and operating expenses) in our efficiency models.

Table 2 presents the descriptive statistics of the main variables used in the DEA analysis; in Table 3, these are also shown by year (only for the full data sample). We observe that, although all of the output variables exhibit decreasing trends over time, with respect to inputs, only the average number of beds decreases over time, from an average of 234 in 1999 to an average of 211 in 2010. All of the other input variables measuring hospital staff exhibit an increasing trend over the period. This picture reflects the de-hospitalization policy pursued in Italy over the past twenty years (Piacenza et al. 2010).

To investigate our research topic, we first consider the different typology of hospitals and, then, we use a set of regulatory variables, which have been shown to capture differences in regional regulatory systems (Cavalieri, Gitto and Guccio 2013; Cappellari, Paoli and Turati 2014; Finocchiaro Castro et al. 2014). In Table 4, descriptive statistics for the variables employed in the second stage are presented. For convenience, full discussion of these variables is postponed to the next sections.

(Insert TABLE 4 about here)

4.3 Empirical strategy

In this paper we employ different approaches to examine the impact of different PPS schemes on hospital efficiency in the Italian regions. In the first step, we use the DEA methodology to measure the technical efficiency of a large sample of Italian hospitals over the twelve-year period between 1999 and 2010.

Following previous studies on hospital efficiency (O'Neill et al. 2008), we use an input-oriented approach where the output levels do not change, whereas the input quantities are reduced proportionately until the frontier is reached. Alternatively, the output-oriented framework aims at maximizing the output levels keeping the inputs constant. In this paper, the input orientation has been preferred as the underlying hypothesis seems quite reasonable in the long term and more consistent with the evidence provided by Piacenza, Turati and Vannoni (2010) concerning the de-hospitalization policy pursued in Italy over the past twenty years.

The DEA technique allows to measure hospitals' efficiency either with respect to a unique frontier estimated by pooling the data (*i.e.* intertemporal frontier approach) or separately by estimating a frontier for each year (*i.e.* contemporaneous frontiers approach*)* (Jondrow et al. 1982). Under the intertemporal frontier approach*,* constant technology over time is assumed; however, as the time span of our sample is rather large, the assumption of time-invariant technology might be somewhat unreasonable. Additionally, the approach does not allow for the identification of year-specific effects. For these reasons, hereafter we employ the more reasonable contemporaneous frontier approach, in which the frontier in each year is constructed based on the observations solely of the current year.[20] Finally, to control for consistency among DEA efficiency estimates, we apply the bootstrapping algorithm proposed by Simar and Wilson (2000).

Once efficiency estimates are obtained, different empirical strategies are considered to investigate our research topic. In line with the approach followed by Barbetta, Turati and Zago (2007), we first apply several non-parametric tests to assess whether hospital type matters for performance. Specifically, we test the hypothesis that HUs are statistically different from all other hospitals (both public and private ones) as far as efficiency scores are concerned.

As a further investigation, we then apply a DEA two-step methodology proposed by Simar and Wilson (2007) to the DEA efficiency scores. Specifically, we estimate the following general models:

$$\theta_{CRS\,it} = hospital\_type_{i,t} + PPS\_{regulation}_{k,t} + REGION_{k,t} + \mathrm{YEAR}_t + \varepsilon_{i,t} \qquad [3]$$

$$\theta_{VRS} = hospital\_type_{i,t} + PPS\_{regulation}_{k,t}) + REGION_{k,t} + \mathrm{YEAR}_t + \varepsilon_{i,t} \qquad [4]$$

[20] To provide robustness to our empirical findings, we also run DEA estimates by using the intertemporal frontier approach. Results are largely comparable with those presented here and are available upon request from the authors.

where i denotes the hospital, k the region and t the year, θ_{CRS} and θ_{VRS} are the efficiency scores obtained under CRS and VRS assumption, respectively. Looking at the employed variables, *hospital_type* denotes different typology of hospitals, *PPS_regulation* is a vector of variables aiming to capture different reimbursement rules at the regional level in time t (for a detailed description of these variables, see the next section). Finally, *REGION* is a vector of region-specific control variables, *YEAR* is a vector of yearly dummy variables and ε is the error term.

Concerning the two-step procedure, Simar and Wilson (2007) suggest to use bootstrap truncated regression in the estimates of [3] and [4]. Banker and Natarajan (2008) propose a different estimator where the two-stage approach can be applied if the inputs are not (too much) correlated with the environmental variables and provide a statistically consistent estimator, which involves nonparametric estimation of productivity in the first stage followed by OLS regression. However, Banker and Natarajan (2008) two-stage approach depends on quite restrictive assumptions on the production process. Therefore, in what follows we use the Simar and Wilson (2007) bootstrap truncated estimator as the baseline model.

5. Results and Discussion

5.1 DEA efficiency estimates

To assess the technical efficiency of Italian hospitals, we estimate different DEA bootstrap models[21]. Specifically, we consider four different production models as shown in Table 5.

(Insert TABLE 5 about here)

[21] Due to lack of space, results are hereafter provided mainly for the full sample. As previously mentioned, we performed all of the estimates also for a balanced subsample of hospitals. Despite the difference in sample dimension, DEA estimates from the balance panel barely confirm all the results from the full sample. Results for the balanced subsample are available upon request from the authors.

Table 6 provides the pairwise correlation matrix for the estimated models, under boh CRS and VRS assumptions. Overall, a high correlation across the different models is observed, under the hypotheses of either CRS or VRS.

(Insert TABLE 6 about here)

Moreover, in Table 7 we provide the results of Mann–Whitney tests concerning the estimated efficiency frontiers among the different models by using Model_1 as a reference point. It can be seen that technical efficiency is unaffected by the choice of the output variables. Thus, since Model_4 is clearly the most comprehensive and, therefore, likely to be the most suited to account for the differences in hospitals' production functions (in particular, among different types of hospitals), in what follows we base our discussion of results only upon the estimates from it. [22]

(Insert TABLE 7 about here)

Finally, the kernel density functions, reported in Figures 2 and 4, show that, from the perspective of sensitivity analysis, the efficiency estimates under both scale assumption are quite robust with respect to sampling variation since there are only small differences between biased and biased corrected efficiency estimates.

5.2 Preliminary findings

The average DEA efficiency scores for the full sample by year and type of hospital are presented in Table 8, under both CRS and VRS assumptions. Similarly, the distribution of the DEA efficiency scores by type of hospital and year, as well as the Kernel density of the efficiency scores, are shown in Figures 1 to 4, under CRS and VRS assumptions, respectively. To address the problem that DEA efficiency scores are estimated from a finite sample and, thus, subject to sampling variation of the frontier, we implement a

[22] The results also hold for model_1, model_2 and model_3; related tables are available upon request from the authors.

bootstrap procedure, with 200 bootstrap draws, as described by Simar and Wilson (1998). This procedure allows us to correct the bias in DEA estimators and to obtain unbiased confidence intervals. Figures 2 and 4 present Kernel density estimates of the efficiency scores that rely on the reflection method, before and after the bootstrap correction and under different scale assumptions (Simar and Wilson 2008). [23]

(Insert TABLE 8 about here)

(Insert FIGURE 1 about here)

(Insert FIGURE 2 about here)

(Insert FIGURE 3 about here)

(Insert FIGURE 4 about here)

From the upper part of Table 8 and from Figure 1 (CRS model), no significant differences appear in the efficiency levels between those hospitals directly managed by LHAs (*i.e.* HUs) and all the other types of hospitals. However, as emphasized by the previous literature on the topic, the assumption of constant returns to scale might not represent a proper specification for a hospital production function, being variable returns to scale more appropriate for healthcare services. If the latter is the case, as Italian hospitals exhibit significant differences in average size, then CRS efficiency scores could be particularly affected by the wrong specification of the returns to scale.

On the empirical ground, the hypothesis of non-constant returns to scale seems to be confirmed by the VRS efficiency scores shown in the lower part of Table 8 and in Figure 3. Compared to the CRS ones, VRS efficiency scores exhibit larger differences among types of hospitals. Particularly, looking at the median efficiency score values, hospital trusts turn out to be the most efficient typology of public hospitals, while HUs result the less efficient one. This piece of evidence is especially relevant for the

[23] By doing so, we were able to avoid problems of bias and inconsistency at the boundary of support (Simar and Wilson 2008).

objective of this study, given that, as previously mentioned, hospitals directly managed by LHAs (*i.e.* HUs) are the only ones to be financed by global budget, whereas all of the other Italian hospitals are financed by DRG-based PPSs.

Again from the lower part of Table 8 and from Figure 3, hospital units seem to be more efficient than accredited private for-profit hospitals, despite the fact that the latter are effectively financed by PPS. This apparently counter-intuitive result could be due either to the choice of the selected output variables or to the great heterogeneity existing among private hospital structures. Looking at the variability of the efficiency scores within a given typology of hospitals (Figure 3), however, the latter seems the most reasonable explanation. Indeed, accredited private for-profit hospitals show the greatest variability of scores while hospital trusts exhibit the smallest one.

It should be also considered that VRS efficiency scores, apart from the pure technical efficiency of production units, also include the efficiency scale with respect to the best production frontier. As Italian accredited private for-profit hospitals tend to be small in size and, thus, significantly below the efficient scale of production for healthcare services, they might be technically efficient but still exhibit lower VRS efficiency scores. To control for this problem, we perform the Banker's test (Banker 1996) on scale assumptions. The results reject the null hypothesis of CRS at any conventional level of significance. [24]

Finally, as an attempted step of this first stage of the efficiency analysis, we test the hypothesis that HUs are statistically different from all other hospitals (both public and private ones) as far as efficiency scores are concerned. To this purpose, we compute the two-sample Kolmogorov-Smirnov's test for the equality of distribution of DEA efficiency scores between hospital directly managed by LHAs (i.e. HUs) and all other hospital types working on behalf of the Italian NHS. For the sake of completeness, we

[24] Results are available upon request from the authors.

run this test for either CRS or VRS efficiency scores. Indeed, all different tests report a p-value = 0.000, implying a significant difference in the distribution of DEA efficiency scores between HUs and all the other typologies of hospitals.

Finally, we also compute the Bartlett's test (Snedecor and Cochran 1983) for the equality of variances between the efficiency scores of HUs and all other types of hospitals. Again, the test show always a p-value = 0.000, meaning that the variance of DEA efficiency scores between these two categories of hospitals (HUs and all other hospitals) is significantly different.

5.3 Second stage analysis

In this section, we apply a two-stage analysis, to evaluate more in depth whether different categories of hospitals show different performances depending on their financing mechanisms. More specifically, we regress the DEA efficiency scores, under the hypothesis of both CRS and VRS, against hospital categories, using hospitals directly managed by LHUs (*i.e.* HUs) as the omitted category, since they are not actually financed by tariffs. Although, the Banker's test strongly favors VRS technology in our sample, we provide also the estimates with respect to the CRS assumption, since these represent a reference point in the two-stage analysis. Finally, we include regional and time controls.

We apply both semi-parametric (Simar and Wilson, 2007) and parametric (Banker and Natarajan, 2008) robust OLS estimators. Following Simar and Wilson (2007), we estimate the truncated regression models given in [3] and [4] using maximum likelihood.

The Table 9 provides semi-parametric bootstrap truncated (Banker and Natarajan, 2008) robust OLS estimates for the full sample, under the hypothesis of CRS. Similar estimation results under VRS assumption are reported in Table 10.

(Insert TABLE 9 about here)

(Insert TABLE 10 about here)

Looking at the estimates under CRS in Table 9, we do not find general evidence that hospitals paid by tariffs exhibit higher efficiency levels than HUs. This is especially true when the more robust semi-parametric estimates are considered. However, moving to the VRS hypothesis, estimation results change consistently. The results in Table 10 show that hospital trusts perform significantly better than HUs. This is also the case for not-for-profit hospitals. However, in both cases, accredited private for-profit hospitals are significantly less efficient than our baseline category. As previously predicted, this surprising result could be due to the fact that, for this typology of hospitals, there seems to exist an excess capacity problem, mainly in terms of hospital beds. Therefore, the specification used in the analysis could systematically penalize these type of hospitals. However, this result could be also due to hospital specific characteristics that are not captured by our estimators due sample composition. As a robustness check of these results, we re-run our estimates using the balanced subsample balanced 492 hospitals over the twelve years, comprising 5,904 observations. The results in Table 11 for the VRS largely confirm the previous ones.

(Insert TABLE 11 about here)

Since one could argue that in the previous estimations we did not account properly for differences in hospital financing mechanisms among regions, in the following we will explore the determinants of efficiency at regional level. In Figure 5, boxplots for the efficiency scores by regions, under the hypotheses of both CRS and VRS, are provided. Results show that significant differences exist among hospitals located in different regions. Once again, it is worth to mention that Italian regions adopt the tariff system only to finance public independent and private accredited hospitals, whereas hospitals managed by LHAs (*i.e.* HUs) are completely outside the tariff mechanism. However, the extent to which the DRG per case payment system is used by each region varies greatly among regions. To evaluate the effects of the differences existing among the regional funding systems on hospital efficiency, we use a set of regulatory variables, which have been shown to be able to capture differences in regional regulatory systems (Cavalieri, Gitto and Guccio 2013; Cappellari, Paoli and Turati 2014; Finocchiaro Castro et al. 2014). Specifically, as a proxy for the extent to which the DRG per case payment system is used in each region, we consider the share of total hospital beds owned by public independent (hospital trusts) and private accredited for-profit hospitals (DRG_EXTENT). Even if the variable DRG_EXTENT is a very rough representation of the differences in financing systems across Italian regions, it certainly captures the relative size, in each region, of two large groups of hospitals, which are strongly characterized, among others, by differences in management and, above all, in financing. We are well aware that the regional differences in the implementation of the tariff system, within the subset of hospitals including the public independent and private accredited ones, are not fully captured by our DRG_EXTENT variable. Therefore, to capture residual regional differences in the financing mechanism, we distinguish, through a dummy variable, between those regions that have established their own DRG tariffs and those that have opted for the national DRG rates (REGIONAL_DRG).

In Table 12, we re-run the estimates that capture differences in regional regulatory systems, under the VRS assumption. The results show that those regions that have a higher hospital supply financed by an activity based payment system have a higher level of efficiency (the DRG_EXTENT variable is significant and positive), *ceteris paribus*. Moreover, the dummy variable referring to the residual regional differences in the adoption of financing mechanisms (REGIONAL_DRG) is positive and highly significant. Once again, as a robustness checks of our findings, we perform the estimates using the balanced subsample under VRS. The results reported in Table 13 confirm the robustness of the main findings of our analysis.

(Insert TABLE 12 about here)

(Insert TABLE 13 about here)

6. Policy Implications and Final Remarks

This study examined the impact of DRG-based PPS on the efficiency of Italian hospitals. To this end, we carried out a two-stage efficiency analysis, in which the first stage estimated the DEA efficiency scores of all Italian hospitals, and the second stage regressed the scores on specific explanatory variables, aiming to capture the role of regional financing systems.

We conclude from the results that a significant impact of the use of DRG-based PPS on hospital efficiency level exists. In particular, we found evidence that hospitals financed by PPS tend to be more efficient on average than those financed by a global budget. This difference is particularly marked for public hospitals, in which hospital trusts, financed by DRG tariffs, clearly resulted to be more efficient than HUs, which are financed by global budgets. However, the comparison of HUs to accredited private for-profit hospitals is problematic because of the smaller scale as well as the excess capacity problem, mainly regarding hospital beds, of the latter. Moreover, the specification employed in the analysis, which uses case-mix adjusted discharged patients, could systematically penalize accredited private for-profit hospitals.

A controversial issue of our results concerns the interpretation of the decreasing trend of DEA efficiency scores over time. Indeed, the DRG-based PPS was introduced to increase the levels of efficiency of all Italian hospitals. Yet, surprisingly, our findings indicate that efficiency levels began decreasing in 1999. One reasonable explanation for this might be that the introduction of DRG-based PPS in the Italian NHS co-occurred with a significant reshaping of healthcare policies aiming to reduce hospitalization rates. Thus, the decreasing trend in efficiency levels could be caused by the consistent decrease in outputs that were not followed by corresponding reductions in inputs.

Overall, the results of our efficiency analysis seem to support the hypothesis that the introduction of a PPS financing system incentivizes hospitals to be more efficient. If so, this empirical evidence from data on the Italian NHS represents further support for the theoretical prediction that the introduction of a PPS should induce hospitals to operate more efficiently.

In conclusion, our analysis provides important implications for healthcare policies. In particular, the introduction of PPS should be considered an effective tool for policy makers to increase hospitals' efficiency in the provision of healthcare services. Furthermore, this tool should be considered effective for any case-mix of providers present in the system. However, our evidence on the efficiency of Italian private hospitals suggests that the increase in technical efficiency induced by the introduction of PPS might not be enough to overcome the low efficiency related to a small scale of production. Consequently, a health system with a considerable proportion of private providers should attend to the scale of production of each hospital operating within it. Finally, healthcare policies aiming to lower hospitalization rates while avoiding inefficient waste of resources should ensure that the induced reduction in outputs does not generate an excess of capacity and, rather, correlates with a reduction in inputs.

Although our empirical findings are robust with respect to several statistical checks, the conclusions that can be drawn by this study are tentative, and several issues are open to scrutiny. Above all, this study evaluates efficiency by using imperfect output proxies. In addition, a more appropriate evaluation of the impact of DRG-based PPSs would involve outcomes, despite the potential trade-off between quality and technical efficiency. Last but not least, as emphasized by our findings, further research and analyses are needed to identify the short-term and long-term effects of PPS reforms on healthcare systems.

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Tables

Table 1. Sample Composition by Type of Hospital (Full data sample and subsample of balanced panel data)

Type	Full data sample		Subsample of balanced panel data	
	No. Obs.	*%*	*No. Obs.*	*%*
Hospital Trusts	1,036	9.09	431	7.30
Hospital Units	5,365	47.09	2,616	44.31
Private For Profit Hospitals	3,962	34.78	2,189	37.08
Not For Profit Hospitals	1,030	9.05	668	11.31
All sample	**11,393**	**100.00**	**5,904**	**100.00**

Source: our elaboration on data provided by the Italian Department of Healthcare.

Table 2. Descriptive Statistics for the Selected Variables in DEA models (Full data sample and subsample of balanced panel data)

Variables	Full data sample		Subsample of balanced panel data	
	Mean	*S.D.*	*Mean*	*S.D.*
Inputs				
Beds	217.99	261.77	224.28	269.28
Physicians	119.00	158.67	125.02	170.69
Nurses	262.76	374.69	267.04	384.42
Other personnel	236.39	366.04	241.56	378.37
Outputs				
Inpatient days	6,0784.15	7,9267.27	6,2330.11	8,2381.26
Discharged patients	8,489.08	10,088.61	8,704.14	10,411.26
Case-mix adjusted discharged patients	7,797.36	10,172.41	7,995.23	10,576.92

Source: our elaboration on data provided by the Italian Department of Healthcare.

Table 3. Descriptive Statistics for the Selected variables by Year (Full data sample)

Years	No. Obs.	Beds		Physicians		Nurses		Other personnel		Inpatient days		Discharged patients		Case-mix adjusted discharged patients	
		Mean	*S.D*	*Mean*	*S.D*	*Mean*	*S.D*	*Mean*	*S.D*	*Mean*	*S.D*	*Mean*	*S.D*	*Mean*	*S.D*
1999	1,044	233.6	288.1	100.8	144.9	236.5	342.4	218.6	342.1	64,629.0	85,120.1	8,968.1	10,746.8	8,309.5	10,944.1
2000	1,020	229.0	282.5	102.4	145.1	239.4	349.6	222.3	350.5	63,283.3	83,066.9	8,835.0	10,568.8	8,193.1	10,754.4
2001	1,012	226.5	276.4	106.9	147.8	248.7	363.8	227.1	353.4	62,104.7	81,948.1	8,803.7	10,471.3	8,135.3	10,734.6
2002	1,004	216.8	261.5	111.4	155.4	249.6	365.9	229.7	363.1	59,856.5	78,477.6	8,515.5	10,101.5	7,844.6	10,285.0
2003	981	214.0	253.8	115.1	155.5	254.5	365.3	235.5	369.9	58,206.7	75,885.2	8,214.2	9,774.6	7,557.6	9,853.0
2004	901	223.4	262.5	124.1	159.5	270.1	381.3	250.2	383.2	61,633.4	78,873.0	8,656.6	10,110.9	7,947.1	10,170.0
2005	904	222.8	261.7	127.4	165.4	266.5	375.5	256.9	402.4	61,887.0	78,514.6	8,648.8	10,064.3	7,906.6	10,030.9
2006	896	199.4	238.2	116.1	155.6	245.9	350.7	210.6	323.5	55,662.1	72,886.4	7,868.0	9,381.3	7,130.0	9,336.4
2007	930	213.2	252.9	128.8	166.0	280.1	394.7	243.6	371.6	60,235.2	78,670.4	8,356.2	9,979.2	7,647.8	9,988.5
2008	914	212.3	252.1	131.6	167.1	286.4	399.6	245.8	371.9	60,814.2	79,120.8	8,360.6	9,972.2	7,654.3	9,958.4
2009	902	209.6	248.7	133.8	168.2	289.9	400.3	249.5	379.9	60,264.5	78,432.3	8,305.8	9,903.4	7,584.5	9,871.0
2010	885	210.9	249.5	137.2	171.2	296.2	406.6	253.3	379.7	60,037.6	78,130.0	8,194.6	9,712.1	7,496.3	9,755.3
All	11,393	218.0	261.8	119.0	158.7	262.8	374.7	236.4	366.0	60,784.2	79,267.3	8,489.1	10,088.6	7,797.4	10,172.4

Source: our elaboration on data provided by the Italian Department of Healthcare.

Table 4. Main Variables Employed in the Second Stage (Full data sample)

Variables	Definition	Mean	St. Dev.
DRG_EXTENT	Proportion of total beds owned by public independent and private accredited hospitals, at regional level	0.475	0.228
REGIONAL_DRG	Dummy variable for regional DRG	0.336	0.474
Hospital Trusts	Dummy variable for hospital trust	0.091	0.288
Hospital Units	Dummy variable for hospital unit	0.471	0.499
Private For Profit Hospitals	Dummy variable for private hospital	0.348	0.476
Not For Profit Hospitals	Dummy variable for other hospitals	0.090	0.287

Source: our elaboration on data provided by the Italian Department of Healthcare.

Table 5. Estimated DEA Models

Variables	Model 1	Model 2	Model 3	Model 4
Inputs				
Beds	X	X	X	X
Physicians	X	X	X	X
Nurses	X	X	X	X
Other personnel	X	X	X	X
Outputs				
Inpatient days		X	X	X
Discharged patients			X	X
Case-mix adjusted discharged patients	X	X		X

Source: our elaboration on data provided by the Italian Department of Healthcare.

Table 6. Correlation Between Efficiency Scores in Estimated Models (Pearson correlation coefficients - Full data sample)

Model	Scale	Model 1		Model 2		Model 3		Model 4	
		CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
Model 1	CRS	1.0000							
	VRS	0.9311*	1.0000						
Model 2	CRS	0.9517*	0.7341	1.0000					
	VRS	0.7311	0.8901*	0.9109*	1.0000				
Model 3	CRS	0.9371*	0.7281*	0.8044*	0.5712	1.0000			
	VRS	0.8088*	0.8770*	0.7107	0.6632*	0.8427*	1.0000		
Model 4	CRS	0.8932*	0.7173*	0.9001*	0.6311	0.7981*	0.7622*	1.0000	
	VRS	0.6732	0.8042*	0.6473	0.7719*	0.5934	0.6934*	0.9501*	1.0000

Source: our elaboration on data provided by the Italian Department of Healthcare.

Note: *: coefficients are significantly different from zero at the 99% confidence level.

Table 7. Results of Mann–Whitney Tests on the Differences Between the Technical Efficiency (TE) and Scale Efficiency (SE) of Hospital Units Between Models

Hypothesis tested	
(H_0) = equality distribution	(*p-value*)
Technical efficiency (TE)	
Model 1 *vs.* Model 2	(0.2841)
Model 1 *vs.* Model 3	(0.1340)
Model 1 *vs.* Model 4	(0.2010)
Scale efficiency (SE)	
Model 1 *vs.* Model 2	(0.3707)
Model 1 *vs.* Model 3	(0.0947)
Model 1 *vs.* Model 4	(0.1443)

Source: our elaboration on data provided by the Italian Department of Healthcare.

Table 8. Average DEA Efficiency Scores by Year and Type of Hospital (Full data sample – CRS and VRS estimates)

CRS DEA efficiency estimates													
Hospital type	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**ALL**
Hospital Trusts	0.4903	0.5290	0.5352	0.6206	0.5438	0.5594	0.6939	0.5813	0.5934	0.6115	0.5720	0.5957	0.5757
Hospital Units	0.5466	0.5573	0.5681	0.6117	0.5243	0.5729	0.6815	0.5759	0.5950	0.5975	0.5818	0.5791	0.5803
Private For Profit Hospitals	0.6111	0.5898	0.6447	0.6316	0.5426	0.5561	0.6030	0.5133	0.5405	0.5344	0.5311	0.5020	0.5657
Not For Profit Hospitals	0.5309	0.5519	0.5627	0.6353	0.5416	0.5970	0.6957	0.5733	0.6071	0.6145	0.5780	0.5897	0.5901
All sample	**0.5596**	**0.5642**	**0.5884**	**0.6212**	**0.5336**	**0.5675**	**0.6554**	**0.5517**	**0.5758**	**0.5768**	**0.5615**	**0.5528**	**0.5757**
VRS DEA efficiency estimates													
Hospital Trusts	0.8283	0.8087	0.8134	0.8018	0.8066	0.7892	0.7957	0.7543	0.8177	0.7774	0.7949	0.8091	0.8011
Hospital Units	0.6475	0.6465	0.6499	0.6675	0.6433	0.6707	0.7062	0.6427	0.6706	0.6649	0.6631	0.6580	0.6598
Private For Profit Hospitals	0.6758	0.6446	0.7064	0.6893	0.6328	0.6164	0.6534	0.5680	0.6049	0.5990	0.6028	0.5712	0.6294
Not For Profit Hospitals	0.6983	0.6843	0.7044	0.7255	0.7078	0.7228	0.7329	0.6621	0.7483	0.7283	0.7249	0.7343	0.7159
All sample	**0.6767**	**0.6640**	**0.6875**	**0.6929**	**0.6607**	**0.6679**	**0.6985**	**0.6237**	**0.6671**	**0.6565**	**0.6583**	**0.6453**	**0.6671**

Source: our elaboration on data provided by the Italian Department of Healthcare.

Table 9. Semiparametric Bootstrap Truncated and OLS Regression Models (Full sample – CRS)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Semiparametric bootstrap truncated regression			**OLS**		
Hospital Trusts	0.007	0.007	0.005	0.005	0.009**	0.007**
	(0.006)	(0.006)	(0.006)	(0.003)	(0.004)	(0.003)
Private For Profit Hospitals	-0.014***	-0.014***	-0.014***	-0.015***	-0.014***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Not For Profit Hospitals	0.009*	0.015***	0.016***	0.010**	0.016***	0.016***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.572***	0.518***	0.496***	0.580***	0.526***	0.504***
	(0.002)	(0.007)	(0.008)	(0.002)	(0.006)	(0.008)
Regional dummies	no	yes	yes	no	yes	yes
Time dummies	no	no	yes	no	no	yes
Observations	11,393	11,393	11,393	11,393	11,393	11,393

Source: our elaboration on data provided by the Italian Department of Healthcare.

Note: error terms in parentheses , *** p<0.01, ** p<0.05, * p<0.1

Table 10. Semiparametric Bootstrap Truncated and OLS Regression Models (Full sample – VRS)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Semiparametric bootstrap truncated regression			**OLS**		
Hospital Trusts	0.168***	0.179***	0.178***	0.141***	0.154***	0.153***
	(0.007)	(0.007)	(0.007)	(0.004)	(0.005)	(0.005)
Private For Profit Hospitals	-0.031***	-0.029***	-0.027***	-0.030***	-0.029***	-0.027***
	(0.008)	(0.008)	(0.008)	(0.004)	(0.004)	(0.004)
Not For Profit Hospitals	0.062***	0.061***	0.063***	0.056***	0.056***	0.058***
	(0.011)	(0.011)	(0.012)	(0.006)	(0.006)	(0.006)
Constant	0.601***	0.515***	0.497***	0.660***	0.578***	0.560***
	(0.019)	(0.020)	(0.020)	(0.002)	(0.007)	(0.009)
Regional dummies	no	yes	yes	no	yes	yes
Time dummies	no	no	yes	no	no	yes
Observations	11,393	11,393	11,393	11,393	11,393	11,393

Source: our elaboration on data provided by the Italian Department of Healthcare.

Note: error terms in parentheses , *** p<0.01, ** p<0.05, * p<0.1

Table 11. Estimate on subsample of balance panel (VRS)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Bootstrap truncated semiparametric regression			**OLS**		
Hospital Trusts	0.149***	0.129***	0.123***	0.003	0.007	0.013*
	(0.011)	(0.010)	(0.010)	(0.008)	(0.008)	(0.007)
Private For Profit Hospitals	-0.058***	-0.071***	-0.069***	-0.025***	-0.034***	-0.034***
	(0.005)	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)
Not For Profit Hospitals	0.054***	0.030***	0.035***	0.021***	0.006	0.011*
	(0.008)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)
Constant	0.591***	0.529***	0.454***	0.706***	0.632***	0.573***
	(0.003)	(0.007)	(0.009)	(0.004)	(0.008)	(0.010)
Regional dummies	no	yes	yes	no	yes	yes
Time dummies	no	no	yes	no	no	yes
Observations	5,904	5,904	5,904	5,904	5,904	5,904

Source: our elaboration on data provided by the Italian Department of Healthcare.

Note: error terms in parentheses , *** p<0.01, ** p<0.05, * p<0.1

Table 12. Impact of Regional Differences in Hospital Financing (Full sample – VRS)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Bootstrap truncated semiparametric regression			**OLS**		
Hospital Trusts	0.151***	0.129***	0.124***	-0.016	0.004	0.009
	(0.011)	(0.010)	(0.010)	(0.008)	(0.008)	(0.007)
Private For Profit Hospitals	-0.056***	-0.073***	-0.069***	-0.025***	-0.034***	-0.031***
	(0.005)	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)
Not For Profit Hospitals	0.149***	0.129***	0.123***	0.001	0.002	0.011
	(0.011)	(0.010)	(0.010)	(0.008)	(0.008)	(0.007)
DRG	0.051***	0.677***	0.286***	0.043***	0.648***	0.323***
	(0.013)	(0.053)	(0.071)	(0.014)	(0.067)	(0.072)
REG_DRG	0.031***	0.116***	0.084***	0.049***	0.183***	0.068*
	(0.005)	(0.010)	(0.010)	(0.006)	(0.033)	(0.035)
Constant	0.583***	0.516***	0.452***	0.711***	0.628***	0.511***
	(0.003)	(0.007)	(0.009)	(0.007)	(0.008)	(0.012)
Regional dummies	no	yes	yes	no	yes	yes
Time dummies	no	no	yes	no	no	yes
Observations	11,393	11,393	11,393	11,393	11,393	11,393

Source: our elaboration on data provided by the Italian Department of Healthcare.

Note: error terms in parentheses , *** p<0.01, ** p<0.05, * p<0.1

Table 13. Robustness checks – (subsample of balanced panel – VRS)

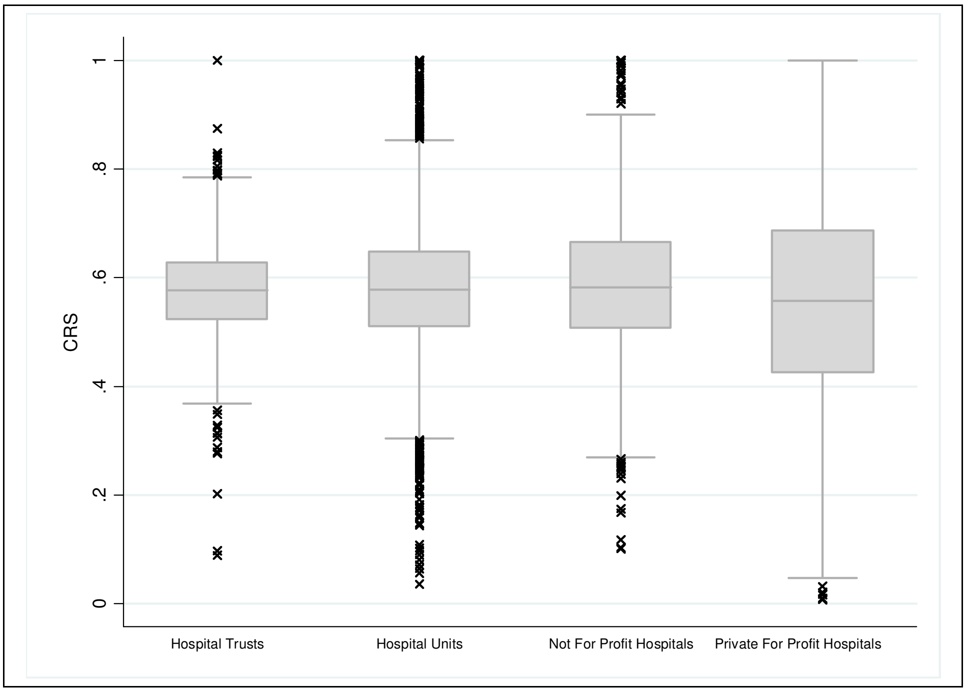
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Bootstrap truncated semiparametric regression			**OLS**		
Hospital Trusts	0.181***	0.201***	0.161***	0.102***	0.095***	0.091***
	(0.016)	(0.015)	(0.015)	(0.006)	(0.006)	(0.007)
Private For Profit Hospitals	-0.019***	-0.034***	-0.034***	-0.021***	-0.038***	-0.038***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Not For Profit Hospitals	0.019***	0.006	0.010	0.055***	0.042***	0.046***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
DRG	0.053***	0.677***	0.286***	0.043***	0.648***	0.323***
	(0.013)	(0.060)	(0.063)	(0.014)	(0.067)	(0.072)
REG_DRG	0.043***	0.109***	0.079***	0.049***	0.183***	0.068*
	(0.005)	(0.011)	(0.010)	(0.006)	(0.033)	(0.035)
Constant	0.580***	0.706***	0.533***	0.686***	0.803***	0.752***
	(0.006)	(0.017)	(0.019)	(0.006)	(0.014)	(0.017)
Regional dummies	no	yes	yes	no	yes	yes
Time dummies	no	no	yes	no	no	yes
Observations	5,904	5,904	5,904	5,904	5,904	5,904

Source: our elaboration on data provided by the Italian Department of Healthcare.

Note: error terms in parentheses, *** p<0.01, ** p<0.05, * p<0.1

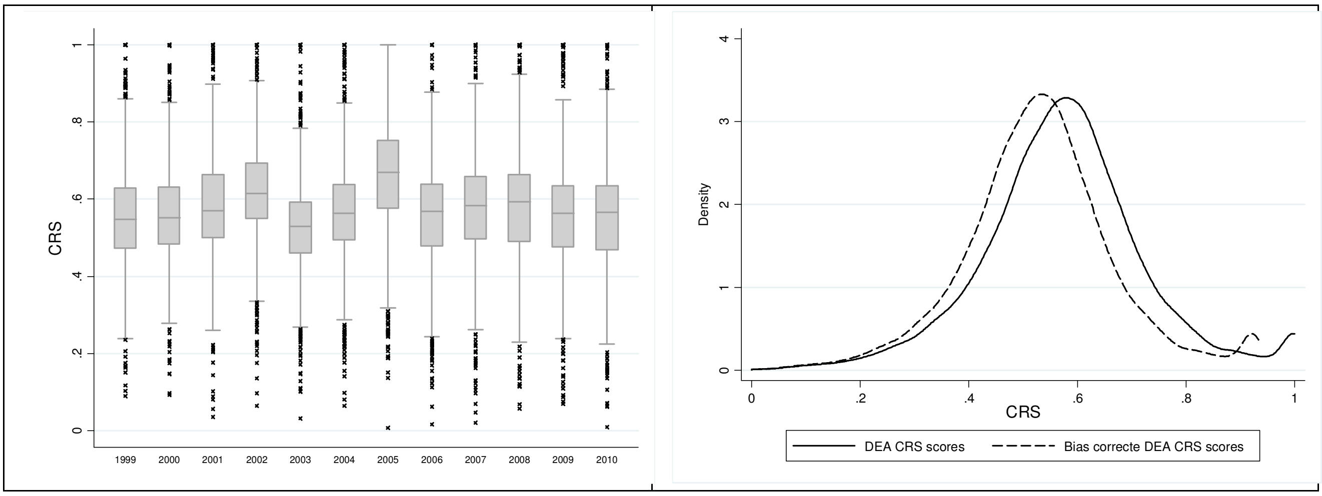
Figures

Figure 1. Box Plots of DEA Efficiency Scores by Type of Hospital (Full data sample – CRS estimates)



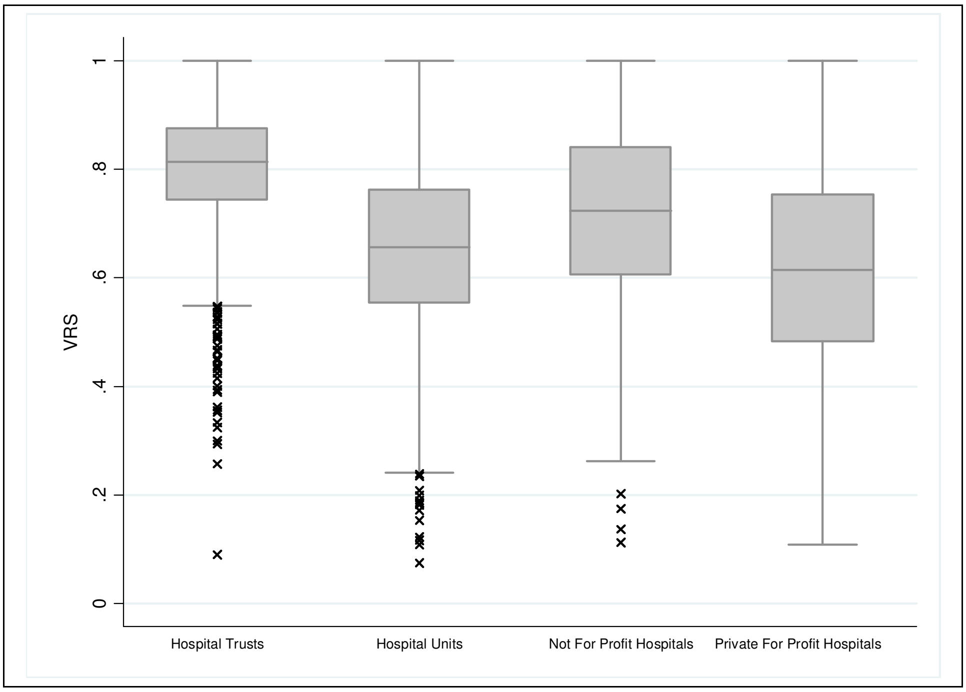
Source: our elaboration on data provided by the Italian Department of Healthcare.

Figure 2. Box Plots of DEA Efficiency Scores by Year (Left) and Kernel Density Estimate (Right) (Full data sample – CRS estimates)



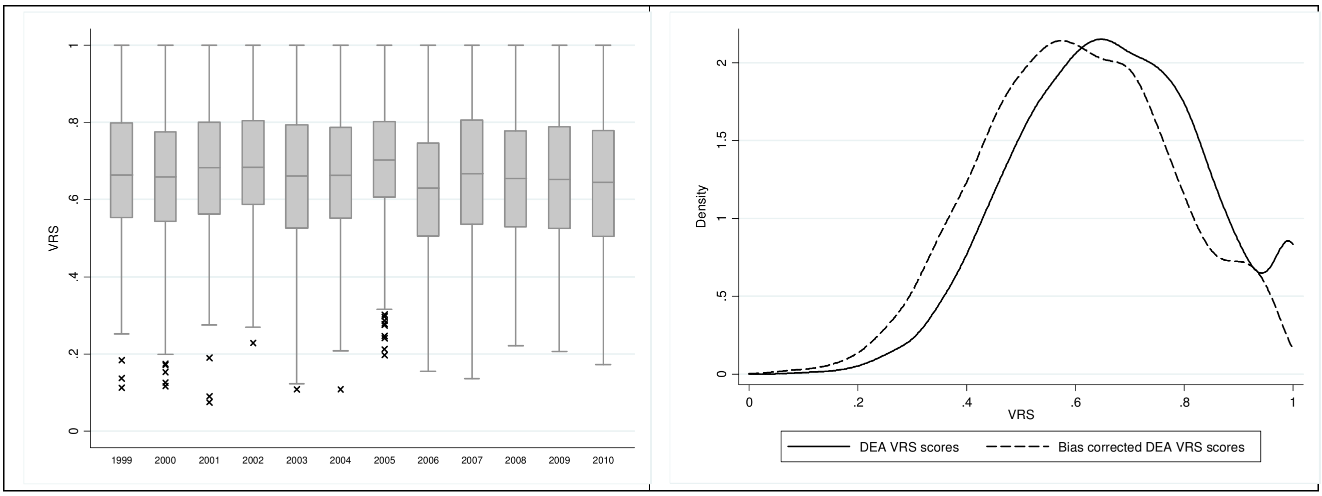
Source: our elaboration on data provided by the Italian Department of Healthcare.

Figure 3. Box Plots of DEA Efficiency Scores by Type of Hospital (Full data sample – VRS estimates)



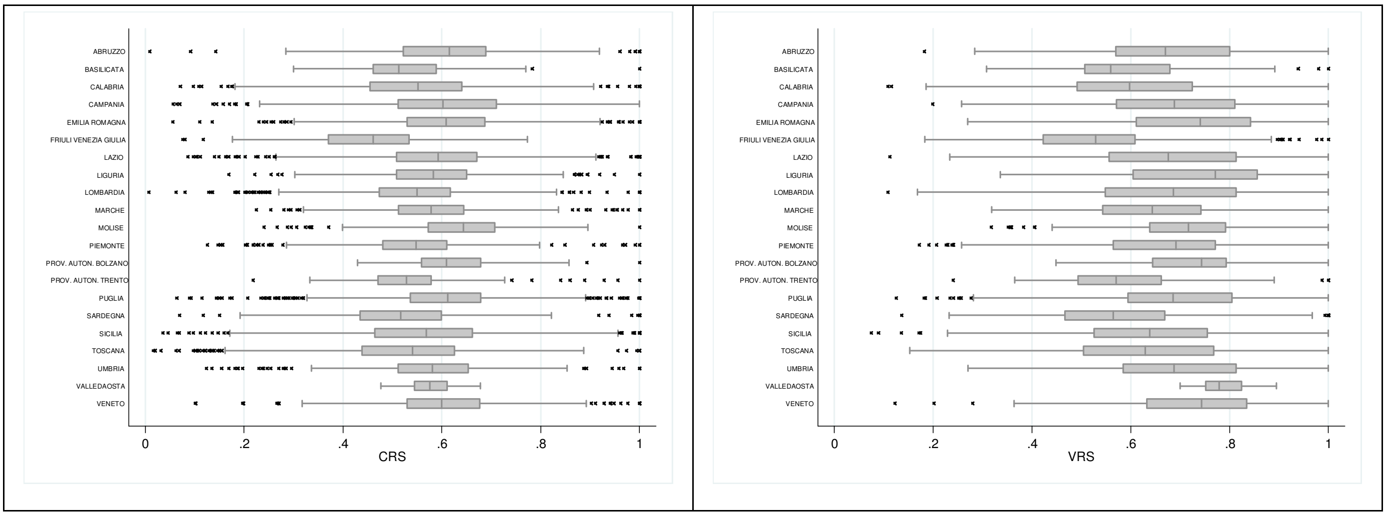
Source: our elaboration on data provided by the Italian Department of Healthcare.

Figure 4. Box Plots of DEA Efficiency Scores by Year (Left) and Kernel Density Estimate (Right) (Full data sample – VRS estimates)



Source: our elaboration on data provided by the Italian Department of Healthcare.

Figure 5. Boxplots of DEA Efficiency Scores by Region –Full data sample - CRS (Left) and VRS (Right)



Source: our elaboration on data provided by the Italian Department of Healthcare.