Università degli Studi di Bergamo

# Efficiency and opportunistic behaviour induced by prospective payment system in the hospital sector

Doctoral Thesis in
Economics and Technology Management

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To my mother

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# Chapter 1

# Introduction

This Doctoral Thesis is an empirical investigation of the Italian hospital sector. The general aim is to analyze the impact of the institutional setting both on hospitals' behaviour and on their efficiency. Since under the Italian Constitution the responsibility for health care is shared by the State and the regions, the latter being in charge of the organization and administration of publicly financed health care, the regional level is the appropriate level of analysis for my purposes. Therefore, I focus on the Italian region of Lombardy.

The Thesis consists of three papers. In the first, I study how hospitals responded to the introduction of prospective payment system in terms of adoption of opportunistic behaviour, and I measure the impact of this distortional factor on technical efficiency by performing an econometric analysis. The second contribution studies the period following a relevant regional health care reform which set the separation between purchasers and providers of health services, creating a form of quasi–market, and investigates the impact of competition on hospitals' efficiency by applying non–parametric techniques. The last paper focuses on the cardiac surgery sector and investigates the effects of tariff regulation on hospitals' behaviour.

The empirical analysis is preceded by a draw of the general framework of Lombard regional health care system in which I briefly describe the evolution of the set of rules.

# Chapter 2

# The Lombardy region institutional setting

Many countries across Europe have introduced decentralization strategies, particularly in the health care sector. In Italy, the responsibility for health care is shared by the State and the regions. The first is in charge of defining the essential levels of care which must be provided uniformly across the regions, while the latter are responsible for organization and administration of health care. Each regional health care system largely differ from the others in terms of prescriptive structure. Lombardy distinguishes itself among the other regions thanks to several peculiarities which will be discussed in the following Sections.

## 2.1 Tariff regulation

Lombardy characterizes itself for a pronounced attitute towards taking its choices and modifying them across the years. Since the introduction of prospective payment system in Italy in 1995, Lombardy adopted its own DRG rates. Furthermore, prices are subject to periodical changes, as shown by the following Table which summarizes the regional decrees issued between 1994 and 2007.

| Decree | |
|---|---|
| N. 62664/1994 | N. 13796/2003 |
| N. 15084/1996 | N. 15324/2003 |
| N. 26367/1997 | N. 18585/2004 |
| N.37597/1998 | N. 19688/2004 |
| N. 941/2000 | N. 20774/2005 |
| N. 30052/2001 | N. 1375/2005 |
| N. 11637/2002 | N. 2645/2006 |
| N. 12287/2003 | N. 3776/2006 |

Table 2.1: Lombardy region tariff regulation

## 2.2 The separation between purchasers and providers of health care services

In 1997 Lombardy underwent a large policy reform.[1] The health care system was reorganized by the creation of a sort of quasi–market through the separation of purchasers (i.e. Aziende Sanitarie Locali) and providers (i.e. Aziende Ospedaliere). Since the, Lombard health care market is characterized by a plurality of equivalent public, not–for–profit and private accredited purchasers.

## 2.3 A regional model patient–oriented and competition–oriented

The regional model adopted in 1997 sanctions the patients' freedom to choose the health services provider among all the accredited hospitals, regardless of the ownership form. This aspect of the reform aims at creating an environment in which hospitals compete to attract patients.

[1] Regional Law N. 29480/1997.

# Chapter 3

# The impact of upcoding, cream skimming and readmissions on hospitals' efficiency. A population–based study

## 3.1 Introduction

In many industrialized countries, the Prospective Payment System (PPS) is a pillar of the health care sector.[1] It has been adopted to improve the sector's efficiency by introducing financial incentives aimed at encouraging a more cost-efficient management of medical care.[2] The PPS, whose effects (and benefits) have been investigated by several contributions,[3] may give rise to

[1]Under the PPS, hospitals receive a pre–determined rate for each admission. Each patient is classified into a Diagnosis Related Group (DRG) according to the clinical information reported in the Hospital Discharge Chart (HDC).

[2]As stated by Barbetta *et al.* (2007), many contributions, especially those investigating the US market, point out that a reimbursement system based on incurred costs does not provide incentives to both cost containment and price competition among hospitals.

[3]The evidence on the effects of PPS in the US is controversial. Coulam and Gaumer (1991) show that a reduction in the number of admissions and in the average length of stay are produced, as expected. Dafny (2005) and Silverman and Skinner (2004) point out that the introduction of the DRG system had a relevant impact on the case–mix of patients treated by hospitals, with opportunistic behaviour exerted by private hospitals. In Italy, France *et al.* (2005) show that Italian hospitals responded to the new incentives introduced by the PPS in different ways according to the ownership form: between 1994 and 2002 the average length of stay fell by 33% in private hospitals and by 8% in public ones; over the same period, admissions fell by 12.5% in public hospitals, but rose by 9.5% in for-profit hospitals.

some distortions, due to the opportunistic managerial behaviour (Barbetta *et al.* (2007), p. 82). Literature has provided several theoretical contributions on these distortions (e.g. Ellis (1998), Barros (2003)), but little evidence is available on their magnitude and, above all, on their effect on hospitals' efficiency. This paper is an attempt to fill this gap in the literature, by developing an econometric analysis to investigate how these distortions influence hospitals efficiency.

In this contribution I focus on three distortions: upcoding, cream skimming and readmissions. The upcoding practice consists in classifying a patient in a DRG that produces a higher reimbursement.[4] Several definitions of cream skimming in the health care sector are available in literature. Ellis (1998) points out that cream skimming consists in the selection of the more lucrative patients;[5] Levaggi and Montefiori (2003) distinguish between cream skimming as patient selection (i.e. "vertical" cream skimming) and cream skimming as treatment selection (i.e. "horizontal" cream skimming). Under the latter practice, the hospital chooses to provide only the more lucrative and less severe treatments. Given the features of the dataset, I focus only on the horizontal definition of cream skimming, i.e. treatment cream skimming. Last, the readmission practice implies that a patient is discharged and then, after a short period, admitted again, so that the hospital receives for the same treatment more than one reimbursement.

These practices are under the hospital management's control, and they may have a substantial impact on its technical efficiency.

The investigation revealed several significant empirical results. First, private hospitals are involved in cream skimming at a much higher rate than public and not–for–profit ones. Second, there is no ownership difference in upcoding, while the use of this distortion is increasing during the period of investigation across all hospital's types. Third, upcoding and cream skimming have a negative impact on the hospitals' output, hence decreasing their overall efficiency. Fourth, readmissions have a positive impact, implying that those hospitals more engaged in this practice have a higher output. However it is likely that this increase in the total number of treatments is due to an

[4]Simborg (1981) defines upcoding or "DRG creep" as a "deliberate and systematic shift in a hospitals reported case–mix to improve reimbursement" by changing the order of the principal and secondary diagnoses.

[5]Ellis (1998) highlights that payment incentives influence both the intensity of services and the patients who are treated. Moreover he identifies three strategies that providers may adopt in response to PPS: "creaming", "skimping" and "dumping". The former strategy is defined as the over–provision of services to low cost patients; skimping is instead the under–provision of services to high cost patients; dumping is the explicit avoidance of high cost patients.

opportunistic managerial behaviour and not to an efficiency effect. Last, my analysis suggests that, contrary to previous investigations (e.g. Zuckerman *et al.* (1994), Vitaliano and Toren (1996), Puig–Junoy (1998), Sloan (2000), Barbetta *et al.* (2007)), public hospitals are less efficient than not–for–profit and private ones.

I achieve these results by applying an econometric analysis to a dataset consisting of the entire population of 134 hospitals within the Region of Lombardy during the period 1998–2007. In Italy health care is managed at a regional level, and many differences exist between the different regional health care systems.[6] In this paper the analysis of the distortions' impact on hospitals' efficiency has been applied to Lombardy, the wealthiest and most populated Italian region.[7]

The dataset does not include information on costs; hence, in order to investigate hospitals' efficiency, I need to estimate a production function, and to measure the deviation of a specific hospital's output from the maximum achievable target. I adopt stochastic frontier models and, in order to test the robustness of the results to different model specifications, I estimate a production function under two functional forms (Cobb–Douglas and Translog) and three econometric models:[8] Random Effects Linear Model (henceforth RE), Pitt and Lee (1981) Random Effects Model (henceforth PL) and True Random Effects Model (henceforth TRE) developed by Greene (2005*a*, 2005*b*).[9]

This work is linked to a limited number of investigations that have studied the impact of different PPS distortions on hospitals' behaviour. Silverman and Skinner (2004) try to estimate whether the use of upcoding is influenced by the form of hospital ownership in US hospitals. They consider only four DRGs and show that upcoding is higher in private hospitals. Dafny (2005) finds instead that US hospitals respond to changes in the DRG prices primarily by upcoding patients. The analysis I perform expands upon these insights in several ways. First, I propose a new proxy to measure upcoding.

[6]The Italian National Health Service (NHS) is controlled by two levels of public authorities: the National Government, who states the main guidelines of the health sector; the Regions, which have the responsibility for the local organization and administration of the health care sector.

[7]Lombardy has a 9.5 million inhabitants (16% of the total) and produces 25% of the Italian GDP.

[8]For a review of studies using stochastic frontier analysis in the health care sector see Hollingsworth (2003) and Rosko *et al.* (2007).

[9]The three different specifications analyze the hospitals' performances under different perspectives: for instance, under the PL model all hospitals have the same technology, but different (time invariant) abilities to optimally exploit it. With the TRE model each hospital has a different technology and its ability to optimally exploit it depends upon time.

Second, I consider all the possible DRG pairs which share the same principal diagnosis but differ for the presence of complications. Third, I expand the scale of previous analyses by running a population–based investigation, which covers about 20 million admissions. Fourth, I use data on comorbidity at the patient level.[10] Cutler (1995) finds evidence, only for some DRGs, of a trend increase in the readmission rate in the US after the introduction of PPS. This contribution extends his analysis by computing the readmission rate for all the possible DRGs, and by proposing a refinement of the readmission's proxy. Louis *et al.* (1999) provide evidence of the impact of PPS on readmissions in Italy. They show that the introduction of PPS does not give rise to an increase in readmission rate. However, the proxy they adopt to compute this distortion may be too wide for medical conditions.

The paper is organized as follows: in Section 3.2 I show the proxies adopted to compute the PPS distortions, in Section 5.4 I present the econometric models. The dataset is reported in Section 5.5, while Section 5.6 presents both some descriptive evidence on upcoding, cream skimming and readmissions according to hospital ownership and size, and the econometric results. The main conclusions of the paper are reported in Section 5.7, which ends up the contribution.

## 3.2 The PPS induced distortions

As mentioned previously, I focus on three distortions: upcoding, cream skimming and readmissions. The first step in the analysis is to design some proxies to compute them. Concerning upcoding, I can start from the contributions provided by Dafny (2005) and Silverman and Skinner (2004). Dafny (2005) adopts the following proxy to compute upcoding: she considers all the DRG pairs defined with and without complications and defines upcoding as the ratio of hospital's discharges in the DRG with complications over the total discharges in the DRG pair (i.e. the sum of discharges with and without complications in a given DRG pair). Her contribution shows that the management changes the intensity of using upcoding in response to variation in the prices reimbursed under PPS, but she does not take into account the fact that the total amount of discharges with complications may be influenced, on top of upcoding, also by the patient's sickness status. If the health status of the population becomes worse, hospitals may register a higher number of patients with complications.

[10]In medicine comorbidity describes the presence in a patient of other diseases in addition to the primary one (see de Groot *et al.* (2003)).

Silverman and Skinner (2004) do consider the patients' status, but do not disentangle it from the proxy they propose for upcoding. They study only four DRGs concerning general respiratory ailments, one of which has a DRG weight much higher than the others because of the presence of complications. Their proxy for upcoding is given by the ratio of hospital's discharges in the DRG with complications and higher DRG weight over the sum (in the same hospital) of the discharges in all the four DRGs considered. In order to take into account the patients' sickness status, Silverman and Skinner (2004) compare the difference in the hospitals' trends for upcoding and Charlson Comorbidity Index. They observe different trends and, consequently, conclude that the increasing trend in upcoding is mainly due to opportunistic behaviour.

I believe that, to identify upcoding, it is necessary to disentangle the share of hospital's discharges with complications between the patients' sickness status and the opportunistic managerial behaviour. For this reason, since I have data on the comorbidity at patient level, I consider a comorbidity index directly in the computation of the upcoding proxy. I adopt the Elixhauser Comorbidity Index (ECI), the index proposed by the Agency for Healthcare Research and Quality (AHRQ) which is utilized in the health sector in Lombardy region.[11] Hence I propose the following proxy for estimating the upcoding distortion:

$$UPCOD_{it} = \frac{s_{it}^C}{s_t^C} \times \frac{1}{ECI_{it}^k} \tag{3.1}$$

where $s_{it}^C$ is the share of discharges in DRGs with complications in hospital $i$ at time $t$[12] and it is calculated as the ratio of the number of discharges with complications over the total number of discharges with and without complications. The term $s_t^C$ indicates the share of DRGs with complications in all the regional hospitals considered at time $t$ and $ECI_{it}$ represents the comorbidity affecting hospital $i$ at time $t$. The exponent $k$ in expression (3.1) is estimated applying the following OLS regression:

[11] Several indexes have been developed to quantify comorbidity (see de Groot *et al.* (2003)), as the Kaplan–Feinstein Index, the Elixhauser Comorbidity Index and the Charlson Comorbidity Index. They consider the coded presence of some secondary diagnoses not linked with the principal one (i.e. the main reason of admission), such as heart attacks, chronic pulmonary disease, diabetes, cancer, AIDS. The Elixhauser Comorbidity Index (see Elixhauser *et al.* (1998)) considers a list of 30 comorbidities, while Charlson Comorbidity Index (see Charlson *et al.* (1987) limited only to a list of 17.

[12] The $19^{th}$ ($14^{th}$) version of the Grouper (the software produced by $3M$ adopted to assign the DRG to each discharge) identifies 96 (90) pairs of DRGs with or without complications.

$$log(s_{it}^{C}) = \alpha + klog(ECI_{it}) + \epsilon_{it} \quad (3.2)$$

Literature does not provide any attempts to estimate the treatment cream skimming. Hence what I present below should be considered as a first attempt to compute it. The index of treatment cream skimming is given by the following expression:[13]

$$CRSK_{it} = \begin{cases} 1 & \text{if } \frac{NDRG_{it}}{NWARD_{it}} \geq \left(\frac{NDRG_t}{NWARD_t}\right)^{90} \\ 2 & \text{if } \left(\frac{NDRG_t}{NWARD_t}\right)^{10} < \frac{NDRG_{it}}{NWARD_{it}} < \left(\frac{NDRG_t}{NWARD_t}\right)^{90} \\ 3 & \text{if } \frac{NDRG_{it}}{NWARD_{it}} \leq \left(\frac{NDRG_t}{NWARD_t}\right)^{10} \end{cases} \quad (3.3)$$

where $NDRG_{it}$ is the total number of DRGs with more than 10 discharges during a year treated in hospital $i$ at time $t$,[14] $NWARD_{it}$ represents the total number of wards in hospital $i$ at time $t$ and $\left(\frac{NDRG_t}{NWARD_t}\right)^{s}$ is the $s^{th}$ percentile of the regional distribution of the ratio between these two indicators in period $t$ (with $s = \{10, 90\}$). The ratio between the number of DRGs and wards takes into account the relationship between the breadth of hospital's inpatient activity and hospital's size. The higher the ratio, the less treatment cream skimming is observed in the hospital. The underlying idea is that the lower the number of DRGs treated per ward in a hospital, the more specialized the hospital is. However, a high value of $CRSK_{it}$ may be due both to health services concentration and to the selection of the more lucrative activities. In order to distinguish these effects, I compare the hospital's number of DRGs per ward with the regional distribution of the same ratio. Hence, I assign a higher degree of cream skimming to those hospitals which have a very low ratio, i.e. less than the $10^{th}$ regional percentile; hospitals with the ratio higher than the $90^{th}$ regional percentile have, instead, a low degree of cream skimming.[15]

Last, I need to design a proxy for readmissions. Cutler (1995) analyzes the impact of some variables related with the treatments provided by hospitals on

[13] The proposed specification has been designed after several interviews performed with regional health officers in charge of the PPS.

[14] In order to reduce the risk of underestimating cream skimming in a specific hospital I consider only the usual hospital activity, and so I rule out of the analysis the DRGs only occasionally treated, i.e. those few discharges on a specific DRG that are treated only under exceptional circumstances. The threshold has been fixed at 10 discharges per year following the suggestions of the regional health care officers.

[15] The index for cream skimming shown in expression (3.3) is discrete. I have also run the analysis shown in Section 5.6 with a continuous index of cream skimming, and I have found no difference in the results.

patient's sickness status after the introduction of PPS in the US . He considers readmissions, computed as the number of discharges in the same hospital during a year. However, since this proxy is computed at the hospital level, it may include a readmission due to a different disease from the initial one, which cannot be classified as a distortion. I believe that two features have to be present for a readmission being classified as the result of a managerial opportunistic behaviour: (1) the readmission has to be for the same disease of the initial admission; (2) it should occur quite shortly after the first discharge. Hence, the proxy I adopt for readmission is the following one:

$$READM_{it} = \frac{y_{it}^T}{y_{it}} \tag{3.4}$$

where $y_{it}^T$ represents the total number of readmissions in the same hospital for the same Major Diagnostic Category (MDC) and within T days from the date of the initial discharge, while $y_{it}$ is the total number of admissions in hospital $i$ at time $t$. In Section 5.6 I will provide some descriptive evidence regarding the proxies presented in this Section.

## 3.3 The econometric models to estimate technical efficiency

Economic theory underlines that technical efficiency is linked with a production function, i.e. the locus yielding the maximum achievable output for a given set of inputs. A production frontier may be estimated using parametric methods. In this contribution I estimate a production function using different functional forms and econometric methods. This allows to test the robustness of the evidence provided.

As mentioned previously, I consider three econometric methods to estimate a production function: the RE model, the PL stochastic frontier model, and the TRE stochastic frontier model. Under the RE model I estimate the following equation:

$$y_{it} = \alpha + \beta x_{it} + b_i + e_{it} \tag{3.5}$$

where $i$ indicates hospital $i$ and $t$ = 1,...,T denotes the year. The dependent variable $y_{it}$ is the observed output of hospital $i$ in period $t$, $\alpha$ is a constant, $\beta$ a vector of parameters and $x_{it}$ an observed vector of covariates for hospital $i$ in period $t$. The error term is split into two components: the term $b_i$, the unobserved random heterogeneity specific to hospital $i$ (constant through time), represents the hospital's inefficiency score and has to be estimated by the model, while the term $e_{it}$ represents the white noise residuals. Under this model each hospital has a time invariant frontier which is identified by a shift in the intercept with respect to a representative hospital, which is its efficiency score (the term $b_i$).

When I study technical efficiency with a PL stochastic frontier model, I estimate the following equation:

$$y_{it} = \alpha + \beta x_{it} + v_{it} - u_i \tag{3.6}$$

where $u_i$ is a one–sided non negative and normally distributed disturbance reflecting the effect of inefficiency, and $v_{it}$ is a two–sided disturbance capturing the effect of noise. The model is estimable by maximum likelihood of the log–likelihood function for the normal–half normal stochastic frontier model (see Greene (2005*b*), p. 283). Under this specification I compute, for each hospital, a maximum output, and so I estimate a frontier for all hospitals. The hospital's inefficiency, given by the term $u_i \geq 0$, is clearly time invariant.

Last, I apply the TRE model, and I estimate the following function:

$$y_{it} = \alpha + \beta x_{it} + w_i + v_{it} - u_{it} \tag{3.7}$$

where $w_i$ is hospital $i$'s specific unobserved random effect (with normal distribution), $u_{it} \geq 0$ is hospital $i$'s time varying inefficiency (with half normal distribution) and $v_{it}$ is the white noise error term. The model is estimable by maximum simulated likelihood (see Greene (2005*b*), p. 288).

The variables I consider to estimate the hospital's efficiency are shown in Table 3.1.

| Variable category | Description | Proxy |
|---|---|---|
| Hospital Output | Case–mix adj discharges | $y^*_{it}$ |
| Hospital Inputs | Beds | $BEDS_{it}$ |
| | Medical staff | $MED_{it}$ |
| | Administrative staff | $ADMIN_{it}$ |
| Ownership | Public | $PUBL_{it}$ |
| | Not–for–profit | $NFP_{it}$ |
| Hospital characteristics | Emergency department | $EMERG_{it}$ |
| | Mono–specialistic | $MONO_{it}$ |
| | Teaching status | $TEACH_{it}$ |
| PPS distortions | Upcoding | $UPCOD_{it}$ |
| | Cream skimming | $CRSK_{it}$ |
| | Readmissions | $READM_{it}$ |

Table 3.1: The variables considered to estimate hospitals' efficiency

The hospital's output is the dependent variable. I consider the number of discharges adjusted for case–mix, with the number of discharges given by the following expression:

$$y^*_{it} = y^{IN}_{it} \times \left(1 + \frac{R^{DC}_{it} + R^{OUT}_{it}}{R^{IN}_{it}}\right) \times AW^{IN}_{it}$$

with $y^*_{it}$ being the total number of discharges case–mix adjusted, $y^{IN}_{it}$ the total number of inpatient discharges, $R^{DC}_{it}$ the day–care revenues, $R^{OUT}_{it}$ the outpatient revenues, $R^{IN}_{it}$ the inpatient revenues and $AW_{it}$ the average DRG weight for inpatient activity of hospital $i$ at time $t$.

The input variables concern beds ($BEDS$), medical staff ($MED$)[16] and administrative staff ($ADMIN$). As pointed out by previous contributions in literature (e.g. Barbetta *et al.* (2007), Dafny (2005) and Silverman and Skinner (2004)), I take into account the impact of ownership (I consider private for–profit hospitals, private not–for–profit hospitals and public hospitals) by computing two dummy variables: $PUBL = 1$ if the hospital is public, and $NFP = 1$ if the hospital is managed by a not–for–profit organization. Moreover, I include some distinctive hospital features, such as the presence of an emergency department (the dummy $EMERG = 1$ if it is present in hospital $i$), the concentration of health services in the treatment of only one pathology (the dummy $MONO = 1$ for cardiological, neurological, oncologic and orthopaedic hospitals) and the presence of a University within the hospital (the dummy $TEACH = 1$ if the hospital has a university teaching status). The distribution of these variables in the sample is described in the next Section. Furthermore, I consider the three distortions described before, i.e. upcoding ($UPCOD$), cream skimming ($CRSK$) and readmissions ($READM$).

Concerning the variable UPCOD, the exponent $k$ of $ECI^k_{it}$ in expression (3.1) estimated by the OLS regression (3.2) , is significant and equal to 1.03. Therefore I assume that $k = 1$. Concerning READM, the estimation has been performed with T = 45 following the suggestions of the regional health care officers who helped me assessing the research project.[17]

As mentioned previously, I consider two functional forms for the production frontier, a Cobb–Douglas model and a Translog model. Under the Cobb–Douglas model, the equation I estimate is as follows:

$$log(y_{it}) = \alpha + \sum_{j=1}^{3} \beta_j log(x_{jit}) + \sum_{l=1}^{5} \gamma_l z_{lit} + \sum_{k=1}^{3} \delta_k d_{kit} \tag{3.8}$$

[16] All labour variables are computed as full time equivalent employees. $MED$ represents the sum of Physicians and Nurses.

[17] In Lombardy region, since 1998 the regional reimbursement system bears a reduction in the unit reimbursement in case of a readmission within 45 days.

where $x_{jit}$ is input $j$ (i.e. beds, medical staff and administrative staff) in hospital $i$ at period $t$, $z_{lit}$ is the characteristic $l$ (i.e. the two dummies for public ownership and not–for–profit ownership, and the dummies for the presence of an emergency department, of mono–specialistic activity and of teaching activity) in hospital $i$ at period $t$, and $d_{kit}$ is the level of distortion $k$ (i.e. upcoding, cream skimming and readmissions) in hospital $i$ at period $t$. Furthermore, I also adopt a translog functional form (see Christensen *et al.* (1973)) for the production function, and in this case the model I estimate is the following one:

$$\begin{aligned} log(y_{it}) = \alpha + \sum_{j=1}^{3} \beta_j log(x_{jit}) + \frac{1}{2} \sum_{j=1}^{3} \beta_{jj} (log x_{jit})^2 + \\ + \sum_{j=1}^{3} \sum_{h=1}^{3} \beta_{jh} log(x_{jit}) log(x_{hit}) + \sum_{l=1}^{5} \gamma_l z_{lit} + \sum_{k=1}^{3} \delta_k d_{kit} \end{aligned} \quad (3.9)$$

where, differently from the Cobb–Douglas function form displayed in expression (3.8), I also estimate both the possible interactions between the hospital's inputs and their second order effects. Hence I estimate six models: two functional forms for the production function and three econometric specifications for each functional form. The results of these models will be displayed in Section 5.6.

## 3.4 The dataset

I investigate a large administrative dataset covering the full population of patients and hospitals operating in the Lombardy Region, with over 20,000,000 admissions, between 1998 and 2007. Given the fact that I use administrative data to investigate the entire population and not a census of it, the sample selection error component of causal estimation error vanishes, as stated by Imai *et al.* (2008).

Table 3.2 shows some descriptive statistics concerning inputs and outputs in the 134 hospitals that compose the dataset. The total number of case–mix adjusted discharges increased during the period, as well as the case–mix index (CMI); on the contrary I observe a decrease in the average length of stay (ALOS). This evidence is consistent with the insights reported in literature (mentioned in the Introduction) concerning some general effects of the introduction of PPS. When I consider the inputs, the total number of beds decreased over the period, showing that the system was running in over–capacity at the beginning of the period. The workforce, on the other hand, increased in all the different categories.

| | 1998 | | | | 2007 | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | St Dev | Min | Max | Mean | St Dev | Min | Max |
| Case–mix adj disch | 13,356 | 14,954 | 567 | 94,350 | 17,523 | 16,523 | 507 | 87,250 |
| Days of stay | 79,025 | 86,634 | 1,178 | 551,999 | 60,003 | 67,443 | 197 | 344,161 |
| ALOS | 7.50 | 3.17 | 3.07 | 34.42 | 6.41 | 3.20 | 0.96 | 21.82 |
| CMI | 0.89 | 0.24 | 0.59 | 2.06 | 1.08 | 0.25 | 0.62 | 2.11 |
| Beds | 316 | 320 | 30 | 2,030 | 262 | 240 | 15 | 1,318 |
| Medical Staff | 500 | 551 | 28 | 2,798 | 512 | 520 | 33 | 2,656 |
| Administrative Staff | 246 | 296 | 3 | 1,718 | 251 | 285 | 5 | 1,399 |

Table 3.2: Descriptive statistics for Lombard hospitals, 1998–2007

In 2007, the average Lombard hospital had a case–mix adjusted output equal to 17,523 (+31% in comparison with 1998), while the total number of days of stay was 60,003 (-24%). The average length of stay was 6.41 days (-14%), and the case–mix index was 1.08 (+21%). Hence, during the analyzed period hospitals increased their output by rising the case–mix index and reducing the days of stay. Concerning capacity, the average hospital had 262 beds (-17%), so that I observe a consistent reduction in hospitals capacity during the period. The personnel is composed of 512 medical staff (+2%) and 251 administrative staff (+2%). Medical staff are approximately two third of total employment.

## 3.5 Results

In this Section I present the results of the empirical analysis. I split the evidence in three parts. First (3.5.1) I display some descriptive statistics about the three distortions, and their distribution across different hospitals according to the variables of ownership type and size. Second (3.5.2), I present the results of the econometric models. Last (3.5.3), I analyze the estimated efficiency scores at hospital level, controlling for the different hospitals characteristics.[18]

[18]The estimation has been performed using the econometric software Limdep 9 and the statistical package SAS.

### 3.5.1 The proxies for the distortions: descriptive statistics

I present now some empirical evidence concerning both the magnitude and the dynamics of the three PPS distortions. Figure 3.1 shows the dynamic of the distortions between 1998 and 2007 in three different hospital ownership types: public, not–for–profit and private (i.e. for–profit).[19] Each picture displays the yearly average distortion per ownership type.[20]

It is evident that the behaviour of the three hospital types regarding the distortions is heterogeneous. The index for treatment cream skimming is much higher for private hospitals, while this distortion is small in not–for–profit and public hospitals. Moreover, the difference seems to become greater with time, since the cream skimming index for private hospitals increases at the end of the period. This new insight confirms some expectations among the profession (i.e. private hospitals do select treatments), but it is the first attempt to quantify them. Another interesting result is that not–for–profit and public hospitals exhibit the same very low level of treatment cream skimming.[21]

The three hospital types demonstrate a rather homogeneous behaviour concerning upcoding, differently from Silverman and Skinner (2004) and Dafny (2005), who reported a higher upcoding level in private hospitals. In this dataset private hospitals were more engaged in this practice only during the period 2003–2005. In the remaining years their behaviour was similar to that of the other hospitals. Moreover, I observe an increasing trend in this distortion and a convergence among the different ownership types during the period of investigation.

Figure 3.1 also shows the general trend for the readmission distortion. All the indices decrease over the period. Not–for–profit hospitals produce a higher distortion, while the private ones show the lowest level: the not–for–

[19]Following the classification adopted by Barbetta *et al.* (2007), I consider as public the public hospital enterprises (Aziende Ospedaliere) and the public research hospitals (Istituti di Ricovero e Cura a Carattere Scientifico pubblici); I classify as not–for–profit hospitals both the private research hospitals (Istituti di Ricovero e Cura a Carattere Scientifico privati) and the hospitals run by religious bodies (Ospedali Classificati), while the private hospitals are the private accredited ones.

[20]The time spell for the upcoding distortion is reduced to the period 2000–2007 because the method to compute the comorbidity index changed in 2000 after the introduction of the $14^{th}$ version of the DRG Grouper, and this modification does not allow to compare the statistics for 1998–1999 with the remaining years.

[21]This evidence is different from Sloan (2000), which argues that for–profit and not–for–profit hospitals are far more alike than different. It is closer to Silverman and Skinner (2004), and the difference between for–profit and not–for–profit hospitals may be due to the presence of altruism (Newhouse (1970)) and vocational purposes.

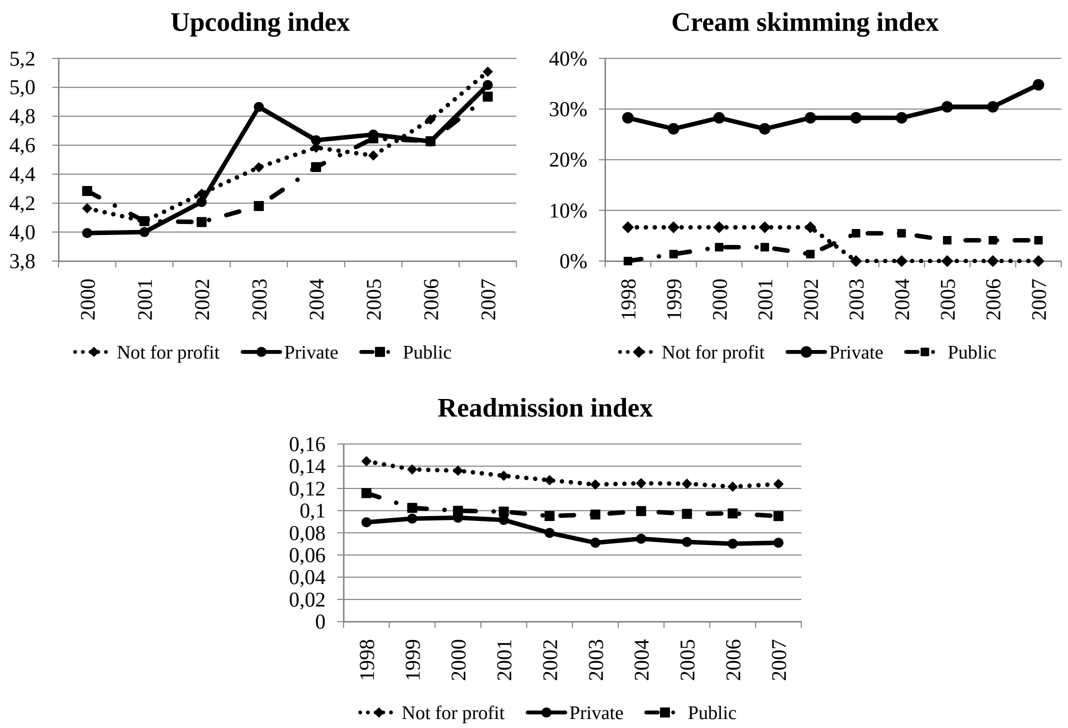


Figure 3.1: PPS distortions by ownership type

profit index is more than double the private one, while public hospitals tend to make more readmissions than private hospitals. I provide two possible explanations for this evidence: (1) more severe controls on the activity of private hospitals on this distortion, which may be more easily checked by the regulator than the previous ones; (2) as mentioned previously, two effects could have an impact on readmissions: reputation and opportunistic behaviour. The reputation effect may be stronger if we consider not–for–profit and public hospitals (see Newhouse (1970), Hansmann (1980)): they have more readmissions because of a better reputation. The latter induces a highest share of less healthy patients, which require repeated and more frequent treatments.

I also present some evidence about the distribution of the three distortions across different hospital sizes, providing some potentially interesting insights on the type of hospitals more likely to be engaged in each distortion. According to the yearly number of discharges, I divide hospitals into three classes: I classify as small hospitals with less than 10,000 discharges; medium hospitals between 10,001 and 30,000 and large hospitals with more than 30,000 discharges. Furthermore, I consider the yearly regional distribution of each distortion and identify the $10^{th}$ and the $90^{th}$ percentile. I classify as highly engaged in a specific type of opportunistic behaviour a hospital with a distortion index higher than the $90^{th}$ percentile.

Figure 3.2 shows the distribution of the different distortions by hospitals size.[22] Small hospitals are characterized by intermediate or high levels in all the distortions considered. 65% (59%) of hospitals showing high (intermediate) upcoding index have less than 10,000 discharges per year. Likewise, 62% (60%) of hospitals showing high (intermediate) readmission index have less than 10,000 discharges per year.

The trend is even more evident for cream skimming: among the hospitals having a high cream skimming index, 73% are very small hospitals (i.e. less than 3,000 discharges per year), and the rate rises to 96% if we consider all the hospitals with less than 10,000 discharges.[23]

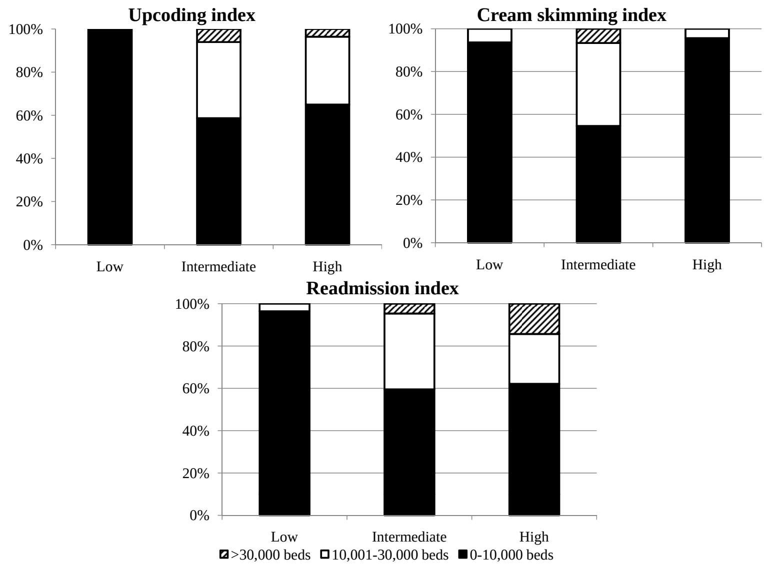


Figure 3.2: Size distribution of PPS distortions

Moreover, if we thoroughly analyze the hospitals showing high cream skimming index, we notice that most of them (95% in 2007) do not have an emergency department (see Figure 3.3), supporting the argument that small hospitals with no emergency department are more likely to select the cases to treat, i.e. to be engaged in treatment cream skimming.

[22]Average values across the period 1998–2007.

[23]Notice that very small hospitals represent 20% of the whole sample and 73% of the hospitals characterized by high cream skimming. Therefore they are significantly more likely to adopt a cream skimming strategy than the others.

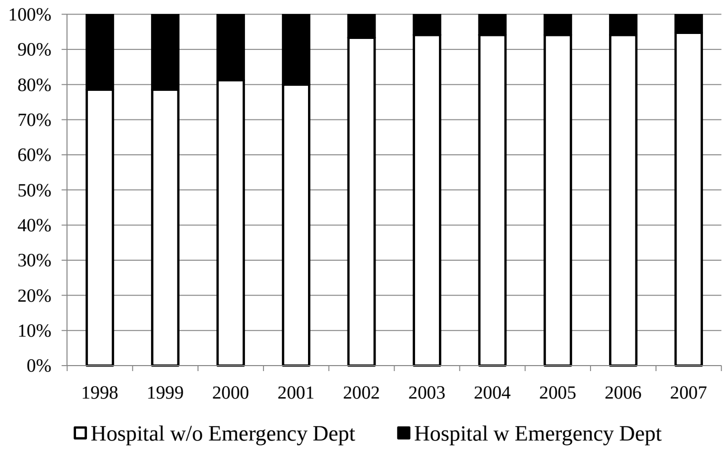


Figure 3.3: Distribution of emergency department in hospitals with high cream skimming

### 3.5.2 The econometric models: results

In this Section I present the results of the econometric estimation. As mentioned previously, for each functional form, i.e. Cobb–Douglas and Translog, I estimate three model specifications, i.e. Random Effects (RE), Pitt and Lee (PL) and True Random Effects (TRE). Moreover, for each functional form and for each econometric specification, I performed two different regressions including different sets of covariates: Model 1 considers only input variables and hospital characteristics (i.e. ownership, presence of emergency department, specialization and teaching status), while Model 2 includes also the proxies for the distortions.

I performed two normality tests on the dependent variable (i.e. the case–mix adjusted discharges). Both the Shapiro–Wilk test and the Kolmogorov–Smirnov test show that we can accept the null hypothesis of normality of output, since the statistics are respectively W=0.99 and D=0.04. Table 3.3 and Table 3.4 display the tests for normality of residuals, correlation among the residuals and homoscedasticity for the two specified functional forms. The Levene's test demonstrates that the residuals are homoscedastic[24]. The Durbin–Watson test reveals a lack of correlation among the residuals.[25] Finally, the Variance Inflation Factor (VIF) index for input multicollinearity shows that inputs are not influenced by multicollinearity.[26]

[24]The $p$–values associated to the Levene statistic are higher than the critical value of 0.01; thus we can accept the null hypothesis of homoscedasticity.

[25]The Durbin–Watson test signals correlation among the residuals if the statistics assumes values $D \leq 1$ or $D \geq 3$.

[26]The VIF indexes are the following: VIF($log(BEDS)$)=6.53, VIF($log(MED)$)=8.73

| | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | RE | PL | TRE | RE | PL | TRE |
| Normality Test | | | | | | |
| Shapiro–Wilk | 0.982*** | 0.951*** | 0.978*** | 0.984*** | 0.953*** | 0.977*** |
| Kolmogorov–Smirnov | 0.057*** | 0.083*** | 0.054*** | 0.053*** | 0.077*** | 0.051*** |
| Correlation Test | | | | | | |
| Durbin–Watson | 1.148 | 1.206 | 1.126 | 1.153 | 1.223 | 1.140 |
| Homoscedasticity | | | | | | |
| Levene | 0.200 | 0.220 | 0.280 | 0.420 | 0.200 | 0.400 |

Significance level: ***¡1%, **¡5%, *¡10%

Table 3.3: Results of the tests on the residuals: Cobb–Douglas functional form

| | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | RE | PL | TRE | RE | PL | TRE |
| Normality Test | | | | | | |
| Shapiro–Wilk | 0.995*** | 0.991*** | 0.993*** | 0.995*** | 0.991*** | 0.994*** |
| Kolmogorov–Smirnov | 0.043*** | 0.036*** | 0.053*** | 0.038*** | 0.032*** | 0.044*** |
| Correlation Test | | | | | | |
| Durbin–Watson | 1.184 | 1.247 | 1.186 | 1.184 | 1.305 | 1.193 |
| Homoscedasticity | | | | | | |
| Levene | 0.480 | 0.530 | 0.030 | 0.030 | 0.400 | 0.090 |

Significance level: ***¡1%, **¡5%, *¡10%

Table 3.4: Results of the tests on the residuals: Translog functional form

The econometric results shown in Tables (3.5)–(3.6) are robust to the different specifications, with few exceptions. In all the models, the input variables are highly significant with positive coefficients, with the exception of administrative staff under the translog functional form. The two input variables having the highest impact on hospitals' output are the number of beds and medical staff, while in each model public hospitals are the least efficient organization. Differently from previous results,[27], not–for–profit hospitals are the most efficient ones under PL and TRE models (there is no difference

and VIF($log(ADM)$)=7.31. The rule proposed by Kutner *et al.* (2004) is that a value of $VIF \geq 10$ is an indication of potential multicollinearity problems.

[27] Vitaliano and Toren (1996) demonstrate there is no significant difference in the estimated inefficiency of hospitals with different ownership. Barbetta *et al.* (2007) show a convergence of mean efficiency scores between not-for-profit and public hospitals. Wilson and Jadlow (1982) find that not–for–profit hospitals are less efficient than profit hospitals but more efficient than public ones. Sloan (2000) demonstrates no systematic differences in efficiency between for-profit and not–for–profit hospitals. Puig–Junoy (1998) and Zuckerman *et al.* (1994) find public and not–for–profit hospitals more efficient than for-profit ones.

between them and profit hospitals under the RE model).

| | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | RE | PL | TRE | RE | PL | TRE |
| Constant | 3.466*** | 4.021*** | 3.931*** | 3.653*** | 4.166*** | 4.033*** |
| | (0.089) | (0.046) | (0.025) | (0.095) | (0.054) | (0.028) |
| LOGBED | 0.572*** | 0.552*** | 0.515*** | 0.568*** | 0.553*** | 0.516*** |
| | (0.023) | (0.01) | (0.007) | (0.024) | (0.012) | (0.007) |
| LOGMED | 0.393*** | 0.376*** | 0.376*** | 0.387*** | 0.368*** | 0.372*** |
| | (0.026) | (0.014) | (0.009) | (0.026) | (0.015) | (0.009) |
| LOGADM | 0.074*** | 0.088*** | 0.083*** | 0.08*** | 0.098*** | 0.089*** |
| | (0.02) | (0.013) | (0.007) | (0.02) | (0.013) | (0.007) |
| T | 0.037*** | 0.037*** | 0.034*** | 0.037*** | 0.037*** | 0.034*** |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) |
| PUBL | −0.289*** | −0.428*** | −0.282*** | −0.314*** | −0.463*** | −0.309*** |
| | (0.045) | (0.026) | (0.009) | (0.044) | (0.025) | (0.009) |
| NFP | 0.048 | 0.102*** | 0.069*** | 0.021 | 0.083*** | 0.036*** |
| | (0.063) | (0.03) | (0.012) | (0.061) | (0.03) | (0.013) |
| EMERG | 0.112** | 0.061*** | 0.161*** | 0.109** | 0.056** | 0.152*** |
| | (0.046) | (0.023) | (0.009) | (0.045) | (0.022) | (0.009) |
| MONO | 0.117 | 0.117 | 0.115*** | 0.123* | 0.085 | 0.117*** |
| | (0.074) | (0.076) | (0.014) | (0.072) | (0.084) | (0.014) |
| TEACH | -0.045 | -0.082 | -0.008 | -0.038 | -0.08 | -0.01 |
| | (0.058) | (0.067) | (0.011) | (0.056) | (0.071) | (0.011) |
| UPC | | | | −0.004** | −0.004*** | −0.002*** |
| | | | | (0.002) | (0.001) | (0.001) |
| CRSK | | | | −0.068*** | −0.061*** | −0.05*** |
| | | | | (0.013) | (0.008) | (0.006) |
| READM | | | | 0.066 | 0.12** | 0.197*** |
| | | | | (0.15) | (0.054) | (0.034) |

Standard errors are given in parentheses. Significance level: ***¡1%, **¡5%, *¡10%

Table 3.5: Results: Cobb–Douglas functional form

[Table 3.6 here]

Regarding hospital's characteristics, the presence of an emergency department increases the efficiency under both functional forms. In fact, it seems that, even though they have to assign, for the presence of an emergency unit, some assets (beds) and labour inputs in order to be able to respond to the peaks in emergency, they are able to admit more patients, and often less healthy and more complicated ones. Under these circumstances the emergency unit generates an increase in the number of admissions.

As expected, mono–specialistic hospitals (i.e. cardiological, neurological, oncologic and orthopaedic hospitals) are more efficient than pluri–specialist ones, even if this result is significant only under the TRE model. The sign of the time variable, capturing the shift in technology, shows an increase in overall technical efficiency, i.e. the regional system became more efficient during the observed period.

Last, I analyze the impact on the hospitals efficiency of the three distortions. Upcoding and treatment cream skimming reduce the hospitals efficiency in all the models. This means that hospitals with high upcoding and treatment cream skimming indices either suffer of a Leibenstein $X-$inefficiency factor, since they obtain higher revenues thanks to the distortions (see Leibenstein (1966)), or they choose to treat less cases to justify the presence of treatments with high DRG weights.[28]

Readmissions have a strong positive impact on efficiency, because, as expected, this practice increases the hospital's output; however, it is likely that this is due to an opportunistic behaviour, not to an efficiency effect.

These results yield some suggestions for changes to the reimbursement policies which will be briefly discussed in the conclusion.

### 3.5.3 The econometric model: analysis of the efficiency scores

I display now the results of the analysis performed on the estimated technical efficiency scores at the single hospital level following the approach suggested by Singh *et al.* (2001). I consider the efficiency scores (i.e. $Exp(-u_i), u_i \geq 0$) estimated under the PL model, using only the inputs as covariates. Hence I compute the average efficiency scores grouping hospitals by the following variables: ownership, presence of emergency department, concentration of health care services provided and teaching status. Last, I perform the Kruskal–Wallis test for testing equality of population means among groups.[29]

Table 3.7 provides a summary of the estimated inefficiency measures. The results of the two different functional forms are similar and consistent with the results of the regressions shown in the previous section. Comparing the three different forms of ownership, not–for–profit hospitals appear to be the most efficient ones, while public hospitals are the least efficient organizations.[30] By running the Kruskal–Wallis test I find evidence that ownership is significantly related to the mean level of efficiency.[31] Table 3.7 also shows

[28]Leibenstein introduces the theory of inefficiency generated from non–competition. It may be summarized as follows: "For a variety of reasons people and organizations normally work neither as hard or as effectively as they could. In situations where competitive pressure is light, many people will trade the disutility of greater effort, or search for the utility of feeling less pressure and of better interpersonal relations." Essentially, there will be a slack in cost control and in the amount of effort put in by management and workers.

[29]Notice that in the PL model inefficiency is assumed to be time invariant, thus we have, for each hospital, only one inefficiency score for all the period.

[30]The efficiency score, defined as $Exp(-u_i)$, is bounded between 0 and 1, where 1 means full efficiency.

[31]The superscript $^{***}$ means that the significance level of the difference between the

that hospitals features like the presence of an emergency department or the hospital's specialization are not significantly related to it.

[Table 3.7 here]

## 3.6 Conclusions

This paper provides some indices to measure three typical PPS distortions: upcoding, treatment cream skimming and readmissions. Moreover, these distortions are introduced as covariates to investigate the efficiency of hospitals in Lombardy, the wealthiest and most populated Italian region.

The main results are the following. First, readmissions are the most relevant distortion, since they significantly increase hospitals' output. Second, cream skimming and upcoding have a negative impact on efficiency. Third, private hospitals are particularly engaged in treatment cream skimming, while this distortion is very low in public and not–for–profit hospitals. Fourth, no ownership differences are observed if we look at upcoding (differently from Silverman and Skinner (2004) and Dafny (2005)), while not–for–profit hospitals make much more readmissions than public hospitals, and the private ones have very low indices. Fifth, differently from previous results reported in literature, not–for–profit hospitals are more efficient than private ones, while public hospitals are the least efficient organizations.

We can draw some policy implications from the above results. First, since upcoding and cream skimming have a negative impact on efficiency, the policy maker may anticipate that hospitals with high upcoding and cream skimming indices have some spare capacity (e.g. too many beds) or more personnel than that required under technical efficiency. This inefficient resources' utilization is due to the management's decision to specialize in the most lucrative treatments. Hence I suggest that the policy maker should use the incentive mechanism in order to try to correct these distortions. One possibility could be the adoption of a reimbursement scheme where the price paid for DRGs with complications (which may be affected by upcoding) is inversely related to the level of the distortion.

Second, hospitals with high readmission index use all the available inputs, since readmissions have a positive impact on technical efficiency. However, they adopt an opportunistic behaviour to increase the total reimbursement. In this case the policy maker should rise the penalty reduction in the reimbursement rate (already implemented in the regional health care service

groups is less than 1%.

I analyzed) in case of a readmission occurred in the same hospital, for the same DRG and shortly after the first admission.

This paper is a first attempt to estimate the impact of some distortions induced by the PPS on technical efficiency. Further research is needed on designing better indices to estimate the distortions (and to include others, e.g. early discharges), and to identify the determinants of the opportunistic behaviour. Furthermore, it is necessary to extend the analysis to hospital's costs and revenues, to identify whether PPS has achieved the goal of costs containment. Last, different regional systems may be considered, to control for cross–regional differences.

## 3.7 Acknowledgments

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| | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | RE | PL | TRE | RE | PL | TRE |
| Constant | 2.04*** | 2.784*** | 2.666*** | 2.24*** | 2.79*** | 2.756*** |
| | (0.345) | (0.181) | (0.104) | (0.353) | (0.194) | (0.112) |
| LOGBED | 1.101*** | 1.111*** | 1.038*** | 1.111*** | 1.138*** | 1.038*** |
| | (0.104) | (0.054) | (0.043) | (0.107) | (0.056) | (0.043) |
| LOGMED | 0.637*** | 0.536*** | 0.585*** | 0.592*** | 0.512*** | 0.569*** |
| | (0.163) | (0.103) | (0.066) | (0.161) | (0.105) | (0.066) |
| LOGADM | -0.129 | -0.138 | −0.149** | -0.133 | -0.125 | −0.151** |
| | (0.132) | (0.088) | (0.06) | (0.13) | (0.092) | (0.06) |
| $(\text{LOGBED})^2$ | −0.257*** | −0.289*** | −0.173*** | −0.263*** | −0.293*** | −0.174*** |
| | (0.045) | (0.032) | (0.018) | (0.045) | (0.032) | (0.018) |
| $(\text{LOGMED})^2$ | 0.159** | 0.164*** | 0.14*** | 0.164*** | 0.167*** | 0.144*** |
| | (0.062) | (0.035) | (0.028) | (0.062) | (0.038) | (0.029) |
| $(\text{LOGADM})^2$ | -0.036 | −0.048* | −0.063*** | -0.045 | −0.054* | −0.065*** |
| | (0.034) | (0.027) | (0.016) | (0.034) | (0.028) | (0.016) |
| LOGBEDLOGMED | -0.074 | −0.062*** | −0.108*** | -0.074 | −0.064** | −0.109*** |
| | (0.054) | (0.023) | (0.023) | (0.054) | (0.027) | (0.023) |
| LOGBEDLOGADM | 0.229*** | 0.242*** | 0.183*** | 0.234*** | 0.245*** | 0.186*** |
| | (0.041) | (0.019) | (0.015) | (0.041) | (0.02) | (0.016) |
| LOGMEDLOGADM | −0.143*** | −0.142*** | −0.076*** | −0.14*** | −0.14*** | −0.076*** |
| | (0.039) | (0.026) | (0.019) | (0.039) | (0.028) | (0.02) |
| T | 0.034*** | 0.034*** | 0.031*** | 0.035*** | 0.035*** | 0.032*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| PUBL | −0.26*** | −0.391*** | −0.251*** | −0.286*** | −0.428*** | −0.276*** |
| | (0.043) | (0.027) | (0.009) | (0.042) | (0.028) | (0.009) |
| NFP | 0.077 | 0.1*** | 0.098*** | 0.041 | 0.066** | 0.064*** |
| | (0.06) | (0.035) | (0.012) | (0.058) | (0.032) | (0.013) |
| EMERG | 0.085* | 0.062*** | 0.148*** | 0.09** | 0.072*** | 0.151*** |
| | (0.045) | (0.024) | (0.009) | (0.043) | (0.024) | (0.01) |
| MONO | 0.039 | 0.134* | 0.063*** | 0.039 | 0.079 | 0.055*** |
| | (0.072) | (0.071) | (0.015) | (0.069) | (0.072) | (0.015) |
| TEACH | 0.039 | 0.098* | 0.063*** | 0.039 | 0.083 | 0.057*** |
| | (0.057) | (0.052) | (0.012) | (0.055) | (0.054) | (0.012) |
| UPC | | | | −0.003* | −0.003*** | −0.002*** |
| | | | | (0.002) | (0.001) | (0.001) |
| CRSK | | | | −0.05*** | −0.045*** | −0.037*** |
| | | | | (0.013) | (0.009) | (0.007) |
| READM | | | | 0.412*** | 0.463*** | 0.376*** |
| | | | | (0.15) | (0.059) | (0.036) |

Standard errors are given in parentheses. Significance level: ***=1%, **=5%, *=10%

Table 3.6: Results: Translog functional form

| | Cobb–Douglas | Translog |
|---|---|---|
| Not–for–profit | 0.712*** | 0.738*** |
| Private | 0.619 | 0.628 |
| Public | 0.503 | 0.536 |
| No EMERG | 0.564 | 0.582 |
| EMERG | 0.568 | 0.595 |
| MONO | 0.564 | 0.589 |
| PLURI | 0.614 | 0.611 |
| Non TEACH | 0.569 | 0.585*** |
| TEACH | 0.547 | 0.637 |

Significance level: ***=1%, **=5%, *=10%

Table 3.7: Hospital inefficiency measures and Kruskal–Wallis test significance

## 3.8 References


- AHRQ, Healthcare Cost and Utilization Project, Comorbidity Software Version 3.3, http://www.hcup-us.ahrq.gov/toolssoftware/comorbidity/comorbidity.jsp.

- Barbetta, G.P., Turati, G. and A.M. Zago, 2007, Behavioral differences between public and private not–for–profit hospitals in the Italian national health service, *Health economics*, 16, 75–96.

- Barros, P., 2003, Cream-skimming, incentives for efficiency and payment system, *Journal of Health Economics*, 22, 419–443.

- Christensen, L., Jorgenson, D. and L. Lau, 1973, Transcendental logarithmic production frontiers, *The Review of Economics and Statistics*, 55, 28-45.

- Charlson, M.E., Pompei, P., Ales, K.L. and C.R. McKenzie, 1987, A new method of classifying prognostic comorbidity in longitudinal studies: development and validation, *Journal of Chronic Diseases*, 40, 373–383.

- Coulam, R.F., Gaumer, G.L., 1991, Medicare's prospective payment system: a critical appraisal, *Health Care Financing Review*, 13, 45–77.

- Cutler, D.M., 1995, The incidence of adverse medical outcomes under prospective payment, *Econometrica*, 63, 29–50.

- Dafny, L.S., 2005, How do hospitals respond to price changes?, *American Economic Review*, 95, 1525–1547.

- de Groot, V., Beckerman, H., Lankhorst, G. and L. Bouter, 2003, How to measure comorbidity: a critical review of available methods, *Journal of Clinical Epidemiology*, 56, 221-229.

- Elixhauser, A., Steiner, C., Harris, D.R., and R.M. Coffey, 1998, Comorbidity measures for use with administrative data, *Medical Care*, 36, 8–27.

- Ellis, R.P., 1998, Creaming, skimping and dumping: provider competition on the intensive and extensive margins, *Journal of Health Economics*, 17, 537-555.

- France, G., Taroni, F. and A. Donatini, 2005, The Italian health-care system, *Health Economics*, 14, S187-S202.
- Imai, K., King, G. and E.A. Stuart, 2008, Misunderstandings between experimentalists and observationalists about causal inference, *Journal of the Royal Statistical Society: Series A*, 171, 481–502.
- Greene W., 2005a, Fixed and random effects in stochastic frontier models, *Journal of Productivity Analysis*, 23, 7-32.
- Greene, W., 2005b, Reconsidering heterogeneity and inefficiency: alternative estimators for stochastic frontier models, *Journal of Econometrics*, 126, 269–303.
- Hansmann, H.B., 1980. The role of nonprofit enterprise, *Yale Law Review*, 89, 835901.
- Hollingsworth, B., 2003, Non–parametric and parametric applications measuring efficiency in health care, *Health Care Management Science*, 6, 203-218.
- Levaggi, R. and Montefiori, M., 2003, Horizontal and vertical cream skimming in the health care market, *DISEFIN Working Paper No. 11/2003*, Available at SSRN: http://ssrn.com/abstract=545583
- Leibenstein, H., 1966, Allocative efficiency vs "X–efficiency", *American Economic Review*, 56, 392–415.
- Louis, D.Z., Yuen, E.J., Braga, M., Cicchetti, A., Rabinowitz, C., Laine, C. and J.S. Gonnella, 1999, Impact of a DRG–based hospital financing system on quality and outcomes of care in Italy, *Health Services Research*, 34, 405-415.
- Kutner, M., Nachtsheim, C. and J. Neter, 2004, *Applied Linear Regression Models*, 4th edition, McGraw-Hill Irwin.
- Newhouse, J., 1970. Towards a theory of non–profit institutions: an economic model of a hospital, *American Economic Review*, 60, 64-74.
- Pitt, M., Lee, L., 1981, The measurement and sources of technical inefficiency in the Indonesian weaving industry, *Journal of Development Economics*, 9, 43-64.
- Puig–Junoy, J., 1998, Technical efficiency in the clinical management of critically ill patients, *Health Economics*, 7, 263–277.

- Rosko, M.D., Mutter, R.L., Stochastic frontier analysis of hospital inefficiency: a review of empirical issues and an assessment of robustness, *Medical Care Research and Review*, 65, 131-166.

- Silverman, E., Skinner, J., 2004, Medicare upcoding and hospital ownership, *Journal of Health Economics*, 23, 369–389.

- Simborg, D.W., 1981, DRG creep: a new hospital–acquired disease, *The New England Journal of Medicine*, 304(26), 1602–1604.

- Singh, S., Coelli, T., 2001. Performance of dairy plants in the cooperative and private sectors in India, *Annals of Public and Cooperative Economics*, 72, 453–479.

- Sloan, F., 2000, Not–for–profit ownership and hospital behavior, in A.J. Culyer, J.P. Newhouse (eds.), *In Handbook of Health Economics*, Volume I. Amsterdam: Elsevier.

- Vitaliano, D.F., Toren, M., 1996, Hospital cost and efficiency in a regime of stringent regulation, *Eastern Economic Journal*, 22, 161–175.

- Wilson, G.W., Jadlow, J.M., 1982, Competition, profit incentives, and technical efficiency in the provision of nuclear medicine services, *Bell Journal of Economics*, 13, 472-482.

- Zuckerman, S., Hadley, J. and L. Iezzoni, 1994, Measuring hospital efficiency with frontier cost functions, *Journal of Health Economics*, 13, 255-280.

# Chapter 4

# Competition and ownership effect on hospitals' efficiency. A Simar–Wilson methodology analysis

## 4.1 Introduction

The analysis of efficiency is a crucial factor of any well designed health care policy. Many reforms have been adopted in the Western countries during the last decades to improve efficiency, given the growing public health expenditures. The analysis of hospitals' efficiency is crucial because it allows the government to optimally allocate resources to hospitals' improvement programs, rather than being subject to lobbies and political pressures. Moreover, benchmarking hospitals against comparable ones helps their managers to understand their competitiveness.

Methods of measuring performance include partial measures of productivity, Total Factor Productivity (TFP) measures and the estimation of efficient frontiers. Partial productivity measures (such as labour productivity) are quite popular since they are easy to compute; however they can be quite misleading, since they do not consider differences in factor prices and depend upon the amount of the other factors involved in production (i.e. they do not take into account the factors' substitutability). TFP are productivity measures involving all factors of production and do not suffer from these drawbacks but are not very informative about management strategies if they are taken alone. Last, an efficient frontier may be estimated both with parametric (e.g. Stochastic Frontier Analysis) and nonparametric methods (e.g. Data

Envelopment Analysis-DEA, Free Disposal Hull–FDH). The estimation of a frontier with econometric methods requires the specification of a functional form for the relationship between inputs and outputs and may produce different results depending on the choice of the functional form.[1] DEA is instead a linear programming technique which infers a piecewise linear production possibility frontier to determine those efficient Decision Making Units (DMUs) that envelop the others. Efficiency measures are then calculated relative to this surface. DEA provides a well–defined relationship between outputs and inputs, which corresponds to a production function, in which the output is maximal for the indicated level of inputs.

The goal of this paper is to analyze the determinants of Lombard hospitals' technical efficiency by applying the two–stage procedure proposed by Simar and Wilson (2007). In the first stage, the efficient frontier is estimated with Data Envelopment Analysis. The DEA method investigates each hospital as a DMU. The DMUs can reflect a whole range of different levels in health care settings, including the entire health care system (Puig–Junoy (1998)), health regions or health districts (Ozcan and Cotter (1994)), Gerdtham *et al.* (1999)), hospitals (Grosskopf and Valdmanis (1987)), specific services or departments (Puig–Junoy (1998), Hollingsworth and Parkin (2001)), and individual physicians (Chilingerian (1994)). In the second stage, the Simar-Wilson double–bootstrap procedure is used to analyze the determinants of efficiency. Efficiency scores calculated for each firm with DEA (i.e. distance from the efficient frontier) are regressed against a set of explanatory variables to extract information about the impact of government decisions (e.g. privatization) or management strategies. Last, I study the productivity change over time by computing the Malmquist index.

This study applies the above mentioned methodologies to estimate the efficiency of Italian hospitals. The sample consists of a balanced panel of 89 public, private and not–for–profit hospitals located in the Lombardy Region and observed during the period 1999–2006. Data include information on different inputs and outputs usually considered in the studies on hospitals efficiency. Input variables comprise the number of hospital beds as a proxy for physical capital and labour inputs measured in full time equivalent employees, disaggregated by skill level in physicians, nurses and administrative staff. Several hospital outputs are specified: case–mix adjusted discharges, case–mix adjusted day–care treatments and number of outpatient visits.

Some contributions have analyzed the efficiency of the Italian health care sector. Cellini *et al.* (2000) investigated the efficiency of about two–third of

[1]Parametric methods need to pre–specify the functional form and are therefore open to specification bias.

the Italian hospitals during a single year (1996), and found that policy reforms that introduced more competition in the Italian health care sector with the aim of increasing its efficiency did not have not a relevant effect. Barbetta *et al.* (2007) studied the efficiency of about one-third of Italian hospitals over a larger period (1995–2000) and suggest that differences in performances between competing ownership forms (i.e. public and not–for–profit hospitals) are due to the external institutional settings where they operate rather than to differences in the internal organization and governance. In this paper I analyze the efficiency of public, private and not–for–profit hospitals operating in Lombardy and take into account a longer period (i.e 1999-2006).

I find evidence that large hospitals are more efficient than small ones, i.e. small hospitals have spare capacity since they are more distant from the frontier than large ones. Moreover, further developments in the activities of large hospitals may lead to an increase in their average costs, since they are mainly operating under decreasing returns to scale.

The truncated regression on the estimated DEA scores shows that efficiency is not influenced by ownership and teaching status. Competition, measured in terms of share of beds per hospital specialty in competition within a ray of 20 km, has a positive impact on hospitals technical efficiency. Activity concentration, measured by the sum of squares of the share of discharges per specialty, has a strong negative impact on efficiency, meaning that those hospitals which specialize and provide a limited number of services are less efficient.

Last, the Malmquist TFP index highlights an increase in the average efficiency in the Italian hospital sector due to a growing capacity of operating at an optimal scale, with a consequent reduction in average costs due to the decrease of the scale of operation.

The paper is organized as follows: in Section 4.2 I describe the proxies adopted for competition and specialization, while Section 4.3 is dedicated to the methodology. Section 4.4 presents the dataset and shows some summary statistics about Italian hospitals. The estimated results about the production frontier and productivity performances are reported in Section 5.6, while the analysis of the determinants of efficiency is performed in Section 4.5.2. The main conclusions of the analysis are reported in Section 4.6, which ends up the contribution.

## 4.2 The proxies for competition and specialization

As mentioned before, I introduce as covariates in the truncated regression some proxies for competition and specialization in order to analyze their impact on hospitals' technical efficiency.

I measure competition among hospitals by computing, for each hospital, the share of beds per specialty in competition with other hospitals within a ray of 20 km. The Competition Index (henceforth CI) I propose is the following:

$$CI_{it} = \frac{\sum_{j=1}^{J} BEDC_{jit}}{\sum_{j=1}^{J} BED_{jit}} \tag{4.1}$$

where $BEDC_{jit}$ is the number of beds for specialty $j$ in hospital $i$ at time $t$ in competition within a ray of 20 km and $BED_{jit}$ is the total number of beds in hospital $i$ at time $t$. The underlying idea is to define an area of 20 km of ray round each hospital.[2] All the hospitals located in this area are the potential competitors. The calculation of the number of beds in competition is performed at specialty level (i.e. internal medicine, cardiology, orthopaedics, surgery). For each specialty $j$, I compare the number of beds in hospital $i$ at time $t$ $BED_{jit}$ to the sum of beds of the $c$ competitors $\sum_{c=1}^{C} BED_{jct}$. The number of beds in competition $BEDC_{jit}$ is calculated as shown in the following equation:

$$BEDC_{jit} = \begin{cases} BED_{jit} & \text{if} \quad BED_{jit} \leq \sum_{c=1}^{C} BED_{jct} \\ \sum_{c=1}^{C} BED_{jct} & \text{if} \quad BED_{jit} > \sum_{c=1}^{C} BED_{jct} \end{cases} \tag{4.2}$$

The underlying idea is that if the number of beds per specialty in hospital $i$ $BED_{jit}$ is lower than the sum of beds of the competitors $\sum_{c=1}^{C} BED_{jct}$, they are all in competition and $BEDC_{jit} = BED_{jit}$. If competitors have a lower number of beds than hospital $i$ per specialty, the number of beds in competition equals the sum of beds of the competitors $\sum_{c=1}^{C} BED_{jct}$, i.e. $BEDC_{jit} = \sum_{c=1}^{C} BED_{jct}$.

To compute specialization, I consider the distribution of discharges among the different specialties and compute the Herfindal Index. The Specialization Index (henceforth SI) I adopt is presented in the following equation:

[2] I select as point of reference a ray of 20 km because statistics reveal that the average distance covered by Lombard patients is equal or less to 20 km in 90% of cases.

$$SI_{it} = \sum_{j=1}^{J} s_{jit}^2 \tag{4.3}$$

where $s_j$ is the share of discharges for specialty $j$ in hospital $i$ at time $t$. The index measures the concentration of inpatient services provided by each hospital. The higher the index, the higher a hospital is specialized.

## 4.3 Methodology

The research instruments adopted in this paper derive from three sources: estimation of efficiency scores, regression analysis of determinants of efficiency and measurement of productivity change across time. Each is considered in turn below.

### 4.3.1 The DEA model and productivity measures

The determination of efficiency in the management of a hospital involves the estimation of a production frontier, so that inefficiency is measured as the hospital's distance from the frontier. In this paper I adopt the non–parametric technique called Data Envelopment Analysis (DEA) where a sequence of linear programming problems creates a piecewise linear frontier, implicitly assuming that outputs can be fully explained from the inputs.[3] According to Barbetta *et al.* (2007) I choose an output orientation, consistent with the fact that in the short run the hospitals are given a fixed amount of resources (in terms of number of beds and employees) and producing as much output as possible can help solving the problem of waiting lists.

The DEA approach has two models: a Constant Returns to Scale (CRS) model and a Variable Returns to Scale (VRS) model, which allow to distinguish between Technical Efficiency (TE), which reflects the ability of a hospital to obtain maximal output from a given set of inputs, and Scale Efficiency (SE), which reflects the hospital's ability to operate at the optimal productive scale.[4] The choice between CRS and VRS usually depends on the context and purpose of the analysis (e.g. managerial benchmarking (VRS) or long-run welfare analysis (CRS)), on the length of the time interval covered by the available data (VRS is more appropriate for a short-run interval), and

[3]Under this approach, the efficiency of a hospital is estimated relative to the performance of other hospitals.

[4]For a discussion on DEA models see Charnes *et al.* (1978), Coelli (1996) and Fre *et al.* (1994).

on the relevance of factors (e.g. regulation) limiting the possibility of operating under the optimal scale of production. Moreover, the size of the available sample may be relevant in the choice between CRS and VRS: for instance, in small samples there are few large units and so, under the VRS model, they tend to be efficient for the simple reason that there are few units to compare. However, in the hospital sector, the importance of factors limiting the possibility of achieving the optimal scale in the short-run justifies the adoption of a VRS model also in this sample.

The CRS model implies solving the following constrained maximization problem for each hospital included in the sample:

$$\begin{gathered} Max_{h,l} h_0 \\ s.t. x_{i,0} - \sum_{l=1}^{L} \lambda_l x_{i,l} \geq 0; i = 1, ...n \\ h_0 y_{j,0} - \sum_{l=1}^{L} \lambda_l y_{j,l} \leq 0; j = 1, ...m \\ h_0, \lambda_l \geq 0 \end{gathered} \tag{4.4}$$

where $L$ is the total number of hospitals, $m$ is the number of outputs considered and $n$ is the number of inputs. The variables $h$ and $\lambda$ represent the weights to be determined by solving the programming model.

The CRS linear programming problem can be easily modified to account for VRS by adding the convexity constraint $\sum_{l=1}^{L} \lambda_l$=1 to equation 4.4 to provide:

$$\begin{gathered} Max_{h,l} h_0 \\ s.t. x_{i,0} - \sum_{l=1}^{L} \lambda_l x_{i,l} \geq 0; i = 1, ...n \\ h_0 y_{j,0} - \sum_{l=1}^{L} \lambda_l y_{j,l} \leq 0; j = 1, ...m \\ \sum_{l=1}^{L} \lambda_l = 1 \\ h_0, \lambda_l \geq 0 \end{gathered} \tag{4.5}$$

Scale efficiency can be obtained for each firm by performing both a CRS and a VRS DEA, and then decomposing the TE scores obtained from the CRS DEA into two components, one due to scale efficiency (SE) and one due to "pure" technical efficiency (i.e. VRS TE). The following equation summarizes the relationship between CRS and VRS TE:

$$TE_{CRS} = TE_{VRS} \times SE \tag{4.6}$$

The difference between CRS and VRS TE scores for a particular hospital are due to the presence of scale inefficiency.

The output–oriented efficiency measures presented above refer to Farrell's (1957) definition of efficiency take a value between zero and one. A value of one indicates the firm is fully efficient.

The following figure displays a graphic representation of the CRS and VRS frontiers for the output–oriented case, and shows the difference between TE an

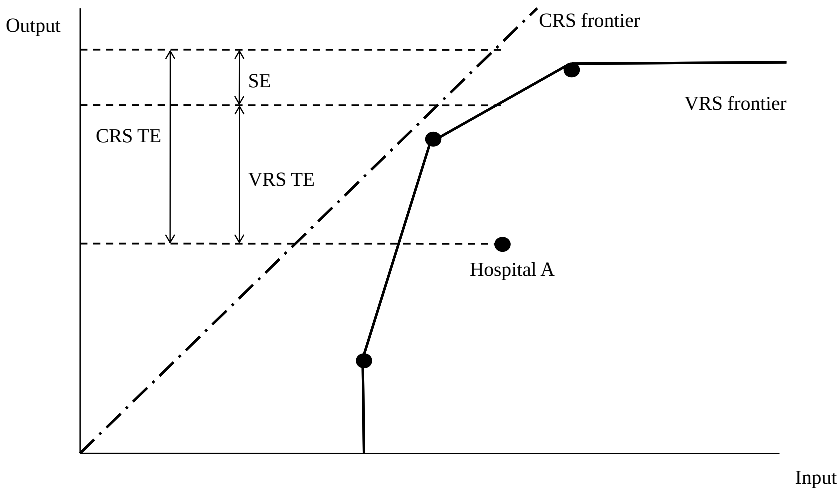


Figure 4.1: Output–oriented DEA, TE vs SE

VRS TE is given by the vertical distance between the location of the generic hospital A and his projection on the VRS frontier. The latter coincides with $h_0$ in the VRS constrained maximization problem 3.5. SE is instead equal to the vertical distance between the projection of hospital A on the VRS frontier and its projection on the CRS frontier. The last projection is obtained by solving equation 3.4. The idea is that, under the CRS model, each unit varies all the inputs, while some of them are constrained under the VRS model. If SE=1 the unit is efficient, since it is on the CRS frontier. If instead SE<1, then we know that VRS are prevailing, but we still ignore the direction of these returns. The latter are identified by running another constrained maximization problem with the following constraint: $\sum_{l=1}^{L} \lambda_l \leq 1$ (instead of $\sum_{l=1}^{L} \lambda_l$=1). If the new estimate of SE<1 and the new $h_0$=(<) $h_0$ under problem 3.5, we have decreasing (increasing) returns to scale.

### 4.3.2 The second stage analysis

The second stage of the analysis incorporates exogenous variables which might influence hospitals' efficiency, like ownership, competition, specialization and teaching status. Introducing exogenous factors of inefficiency is not an easy task. A very recent and useful tool for explaining non–parametric efficiency scores is represented by the two–stage procedure proposed by Simar and Wilson (2007).

The basic idea is to calculate estimates of efficiency in the first stage by DEA and, in a second stage, regress the obtained $\widehat{\lambda}_i s$ against a set of explanatory variables $z_i$. Nevertheless, the authors point out that "many papers have regressed non–parametric estimates of productive efficiency on environmental variables in two–stage procedures to account for exogenous factors that might affect firms' performance" (Simar and Wilson (2007), p.31), but they fail to take into account the following problems of inference:

1. the dependent variable $\lambda_i$ is unobserved and must be replaced by an estimate $\widehat{\lambda}_i$;

2. $\widehat{\lambda}_i$ is a biased estimator of $\lambda_i$;

3. the $\widehat{\lambda}_i$s are serially correlated in a complicated, unknown way;

4. since $x_i$ and $y_i$ are correlated with the $z_i$, the error term $\xi_i$ is correlated with $z_i$.

For these reasons, conventional approaches to inference employed in these papers are invalid. The solution proposed by Simar and Wilson (2007) is the double–bootstrap procedure summarized hereafter:

1. Use the original data to compute $\widehat{\lambda}_i = \widehat{\lambda}(x_i, y_i)$, $i = 1$, ..., n.

2. Use maximum likelihood to obtain an estimate $\widehat{\beta}$ of $\beta$ and $\widehat{\sigma}_\epsilon$ of $\sigma_\epsilon$ in the truncated regression $\widehat{\lambda}_i = z_i\beta + \xi_i \geq 1$, without taking into account the $\widehat{\lambda}_i = 1$.

3. Loop $L_1$ times to obtain n sets of bootstrap estimates $B_i = \{\widehat{\lambda}^*_{ib}\}_{b=1}^{L_1}$, $i$ = 1, ..., n.[5]

[5]I performed 100 replications following Simar and Wilson (2007).

4. For each $i = 1, ..., n$, compute the bias–corrected estimator $\widehat{\widehat{\lambda}}_i$ using the bootstrap estimates in $B_i$ and the original estimate $\widehat{\lambda}_i$

5. Use maximum likelihood to estimate the truncated regression of $\widehat{\widehat{\lambda}}_i$ on $z_i$, yielding estimates $(\widehat{\widehat{\beta}}, \widehat{\widehat{\sigma}})$

6. Loop $L_2$ times to obtain n sets of bootstrap estimates $C = \{(\widehat{\widehat{\beta}}^*, \widehat{\widehat{\sigma}}_\epsilon^*)\}_{b=1}^{L_2}$.[6]

7. Use the bootstrap values in $C$ and the original estimates $\widehat{\widehat{\beta}}$, $\widehat{\widehat{\sigma}}$ to construct estimated confidence intervals for each element of $\beta$ and for $\sigma_\epsilon$.

The application of the double–bootstrap procedure proposed by Simar and Wilson requires that the output–oriented efficiency measures assume the Shepherd (1970) distance function form, i.e. they must be bounded by one and infinity, one meaning full efficiency. Given the fact that an output distance function is defined as the reciprocal of the maximum proportional expansion of the output vector given inputs, we can obtain the Shepherd distance function simply calculating the reciprocal of Farrell efficiency measures.

### 4.3.3 The measurement of productivity change

In order to measure changes in productivity, I use DEA to compute the Malmquist Total Factor Productivity (TFP) index (see *Färe et al.* (1994)). The index evaluates the productivity change between two time periods by calculating the ratio of the distances of each hospital relative to a technology. The Malmquist TFP index between period $t$ and period $t+1$ is defined as the geometric mean of two indexes which use as reference technology, respectively, the period $t$ and the period $t+1$ technology:

$$M_0(y_{t+1}, x_{t+1}, y_t, x_t) = \left[\frac{h_0^t(y_{t+1}, x_{t+1})}{h_0^t(y_t, x_t)} \times \frac{h_0^{t+1}(y_{t+1}, x_{t+1})}{h_0^{t+1}(y_t, x_t)}\right]^{1/2} \qquad (4.7)$$

where $M_0$ is the output oriented total factor productivity index, $h_0^t(y_t, x_t)$ is the output distance function from the period $t$ observation to the period $t$ technology, $h_0^t(y_{t+1}, x_{t+1})$ is the output distance function from the period $t+1$ observation to the period $t$ technology, $h_0^{t+1}(y_t, x_t)$ is the output distance function from the period $t$ observation to the period $t+1$ technology

[6] I performed 200 replications.

and $h_0^{t+1}(y_{t+1}, x_{t+1})$ is the output distance function from the period $t + 1$ observation to the period $t + 1$ technology.

An equivalent way of writing the Malmquist index, useful to specify that TFP change has two components, i.e. Efficiency Change (EC) and Technical Change (TC), is as follows:

$$M_0(y_{t+1}, x_{t+1}, y_t, x_t) = \frac{h_0^{t+1}(y_{t+1}, x_{t+1})}{h_0^t(y_t, x_t)} \times \left[\frac{h_0^t(y_{t+1}, x_{t+1})}{h_0^{t+1}(y_{t+1}, x_{t+1})} \times \frac{h_0^t(y_t, x_t)}{h_0^{t+1}(y_t, x_t)}\right]^{1/2} \tag{4.8}$$

where

$$EC = \frac{h_0^{t+1}(y_{t+1}, x_{t+1})}{h_0^t(y_t, x_t)} \tag{4.9}$$

$$TC = \left[\frac{h_0^t(y_{t+1}, x_{t+1})}{h_0^{t+1}(y_{t+1}, x_{t+1})} \times \frac{h_0^t(y_t, x_t)}{h_0^{t+1}(y_t, x_t)}\right]^{1/2} \tag{4.10}$$

The EC index is equivalent to the ratio of the technical efficiency in period $t + 1$ to the technical efficiency in period $t$ and reflects the degree a hospital attains for improving its efficiency. The TC index is a geometric mean of the shift in technology between two periods and reflects the change in the efficient frontiers enveloping the hospitals between the two time periods. Hence the Total Factor Productivity Change (TFPC) can be written as: $TFPC = EC \times TC$. The intuition underlying the Malmquist index and the two components given by EC and TC can be provided using Figure 4.2.

Suppose that the production of a single output y involves a unique input x, and that there are two observations, at time $t$ and $t + 1$. The two frontiers, relative to $t$ and $t + 1$ technology, are given by $OF_t$ and $OF_{t+1}$, so that there is a shift in the production frontier over time. We also assume that the generic hospital we are considering is inefficient at both periods, given the fact it is located at points A (at time $t$) and B (at time $t + 1$). This implies that the change of this hospital over time depends both on its position relative to the corresponding frontier (i.e. the technical inefficiency or efficiency change EC) and on the position change in the frontier itself (the technological change TC). By applying expression (4.9) we obtain that $h_0^{t+1}(y_{t+1}, x_{t+1})$=CB, $h_0^t(y_t, x_t)$=DA. Hence $EC = \frac{CB}{DA}$. This implies that if EC=1 the hospital has not recovered efficiency during the observed period, while if EC>1 (EC<1) it has improved (decreased) its efficiency. Furthermore, from (4.10) we get: $h_0^t(y_{t+1}, x_{t+1})$=BE, $h_0^{t+1}(y_{t+1}, x_{t+1})$=CB, $h_0^t(y_t, x_t)$=DA, $h_0^{t+1}(y_{t+1}, x_{t+1})$=AF. Hence $TC = \left[\frac{BE}{CB} \times \frac{DA}{AF}\right]^{1/2}$. Again, if TC=1 the distance between the two frontiers at time $t$, computed taking

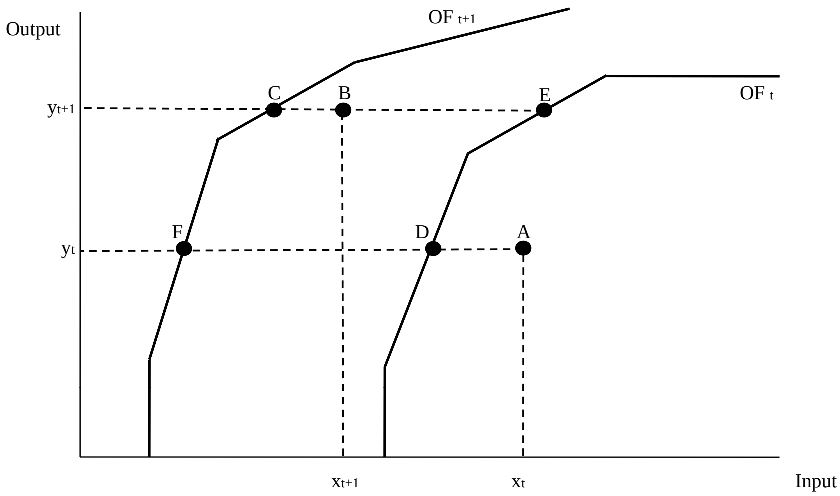


Figure 4.2: Productivity change over time

point A as reference, is equal to the distance between the two frontiers at time $t+1$, taking point B as reference. If instead TC<1 (TC>1) the distance between the two frontiers at $t$ is greater (lower) than the distance between the two frontiers at $t+1$. If TC>1 the hospital has exploited an (exogenous) technical progress.

*Färe* et al. (1994) suggest that efficiency change can be decomposed into a Pure Efficiency Change (PEC) component and a Scale Efficiency Change (SEC), as it follows:

$$PEC = \frac{h_{0v}^{t+1}(y_{t+1}, x_{t+1})}{h_{0v}^{t}(y_t, x_t)} \tag{4.11}$$

$$SEC = \left[\frac{h_{0v}^{t+1}(y_{t+1}, x_{t+1})/h_{0c}^{t+1}(y_{t+1}, x_{t+1})}{h_{0v}^{t+1}(y_t, x_t)/h_{0c}^{t+1}(y_t, x_t)} \times \frac{h_{0v}^{t}(y_{t+1}, x_{t+1})/h_{0c}^{t}(y_{t+1}, x_{t+1})}{h_{0v}^{t}(y_t, x_t)/h_{0c}^{t}(y_t, x_t)}\right]^{1/2} \tag{4.12}$$

The PEC component is measured relative to a VRS frontier. The SEC component is a geometric mean of two scale efficiency change measures, the first is relative to the period $t+1$ technology and the second is relative to the period $t$ technology. The subscripts $v$ and $c$ relate to the VRS and CRS technologies, respectively. Hence the Total Factor Productivity Change (TFPC) can be written as: $TFPC = EC \times PEC \times SEC$ .

## 4.4 The dataset

The data set used in this contribution is a balanced panel of 89 Italian hospitals for the period 1999–2006. The sample covers over 90% of admissions and days spent in Lombard hospitals in this period.[7] The data were provided directly by the Lombard Health Care Council and include information on different inputs and outputs usually considered in the studies on hospitals efficiency. For each hospital I have information on two input variables: the number of hospital beds and the number of day-care beds; labour inputs are measured in full time equivalent employees, disaggregated by skill level in physicians, nurses and administrative staff. For each hospital I have information on the following output variables: case-mix adjusted discharges, case–mix adjusted day–care treatments and outpatient visits.[8]

The variables I used in the analysis are shown in Table 4.1.

| Variable category | Description | Proxy |
|---|---|---|
| Hospital Output | Case–mix adj discharges | $DISCH$ |
| | Case–mix adj day–care treatments | $DC$ |
| | Outpatient visits | $OUT$ |
| Hospital Inputs | Beds | $BED$ |
| | Day–care beds | $DC\_BED$ |
| | Physicians | $PHYS$ |
| | Nurses | $NURS$ |
| | Administrative staff | $ADMIN$ |
| Covariates | Public ownership (dummy) | $PUBL$ |
| | Competition index | $CI$ |
| | Specialization index | $SI$ |
| | Teaching status (dummy) | $TEACH$ |

Table 4.1: The variables

The following table presents descriptive statistics for each output and input variable in the sample data.

Among inputs, between 1999 and 2006 the average number of beds and the administrative employees decreased, while the average number of day–care beds and medical staff increased. In 2006 the typical Lombard hospital has about 400 beds (-25% in comparison with 1999), 227 physicians (+13%), 644 nurses (+4%), 326 administrative employees(-5%).

[7]The data exclude outliers.

[8]Outpatient visits include emergency room treatments.

| | 1999 | | | | 2006 | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | St Dev | Min | Max | Mean | St Dev | Min | Max |
| *BED* | 439 | 465 | 30 | 2,377 | 353 | 327 | 17 | 1,581 |
| *DC_BED* | 35 | 50 | 0 | 208 | 41 | 48 | 0 | 208 |
| *PHYS* | 201 | 226 | 1 | 947 | 227 | 219 | 3 | 926 |
| *NURS* | 618 | 790 | 11 | 3,563 | 644 | 791 | 12 | 3,391 |
| *ADMIN* | 342 | 401 | 3 | 1,852 | 326 | 343 | 5 | 1,696 |
| *DISCH* | 16,709 | 18,242 | 609 | 96,609 | 16,785 | 16,924 | 716 | 81,865 |
| *DC* | 3,863 | 5,879 | 0 | 25,879 | 4,985 | 6,306 | 0 | 31,236 |
| *OUT* | 1,703,921 | 2,195,343 | 0 | 8,247,588 | 1,895,425 | 2,181,982 | 6,419 | 8,884,014 |

Table 4.2: Descriptive statistics for Lombard hospitals, 1999–2006

Among outputs, the inpatient activity is constant from 1999 to 2006 while the day-care and the outpatient activity show an increasing trend. In 2006 the average Lombard hospital performs 16,785 a case–mix adjusted output discharges, 4,985 day–care treatments (+29% in comparison with 1999), while the total number of outpatient visits is roughly 1.9 million (+11%).

## 4.5 Results

In this Section I present the results of the empirical analysis. I split the evidence in three parts. In Section 4.5.1, I show the non–parametric estimates of inefficiency obtained by applying DEA. In Section 4.5.2, I present the results of the second stage regression. Last, in Section 4.6, I analyze the productivity change between 1999 and 2006.[9]

### 4.5.1 The estimates of efficiency

Table 4.3 shows the summary of the results obtained by applying DEA.[10] The estimated efficiency scores are in line with both with Barbetta et al. (2001) and Rebba et al. (2007) results.

Under VRS, in 2006 (1999) we observe 41 (39) hospitals on the frontier, while 30 (25) are on the CRS frontier. This implies that efficient hospitals represent 46% (43%) of the whole sample under VRS, and 34% (28%) under CRS. Both the VRS and CRS technical efficiency scores grow across the analyzed period (with the exception of years 2000 and 2004), underlying an increasing ability of exploiting the scale effect. This is confirmed by the

[9] The estimation has been performed using the Coelli's software DEAP 2.1.

[10] Appendix 1 shows the DEA efficiency scores for all the hospitals in the sample in 1999 and 2006.

fact that scale inefficiency is moving downward across the period and is less than 5% in 2006. Consistently the number of efficient hospitals is raising, especially under a CRS technology. Moreover, we can observe a large increase in the number of firms showing constant returns to scale, counter-balanced by a parallel decrease in the number of firms showing increasing returns to scale. This is an interesting insight since it signals a growing capacity of operating at an optimal scale with a consequent reduction in average costs due to the decrease of the scale of operation.

| Year | CRS Technical Efficiency | VRS Technical Efficiency | Scale Efficiency | CRS Efficient firms | VRS Efficient firms | Firms with IRS | Firms with DRS | Firms with CRS |
|---|---|---|---|---|---|---|---|---|
| 1999 | 0.783 | 0.852 | 0.918 | 25 | 39 | 16 | 47 | 26 |
| 2000 | 0.771 | 0.829 | 00.93 | 23 | 33 | 20 | 45 | 24 |
| 2001 | 0.802 | 0.859 | 0.934 | 24 | 37 | 12 | 51 | 26 |
| 2002 | 0.808 | 0.868 | 0.932 | 26 | 39 | 19 | 41 | 29 |
| 2003 | 0.833 | 0.879 | 0.950 | 25 | 41 | 15 | 46 | 28 |
| 2004 | 0.792 | 0.844 | 0.940 | 22 | 32 | 14 | 52 | 23 |
| 2005 | 0.814 | 0.871 | 0.936 | 26 | 39 | 10 | 51 | 28 |
| 2006 | 0.831 | 0.867 | 0.958 | 30 | 41 | 7 | 48 | 34 |

Table 4.3: Summary of average efficiency scores 1999–2006

If we divide the sample in quartiles (Table 4.4), we can observe that in 1999 the $25^{th}$ percentile (i.e. Q1) is equal to 0.73, meaning that about three quarters of the population are concentrated at a rather short distance from the VRS frontier. During the analyzed period all the sample becomes more efficient, i.e. in 2006 the first quartile shows a technical efficiency equal to 0.81, while a half of the sample has a technical inefficiency lower than 3%.

| | CRS Technical Efficiency | | VRS Technical Efficiency | |
|---|---|---|---|---|
| Quartile | 1999 | 2006 | 1999 | 2006 |
| Min | 0.2 | 0.23 | 0.21 | 0.28 |
| Q1 | 0.64 | 0.72 | 0.73 | 0.81 |
| Q2 | 0.81 | 0.9 | 0.94 | 0.97 |
| Q3 | 1 | 1 | 1 | 1 |
| Q4 | 1 | 1 | 1 | 1 |

Table 4.4: Summary of efficiency scores 1999–2006 by quartiles

Furthermore, if we split the sample in four categories according to the hospital size (Table 4.5), we observe that in 2006 the mean category distance from the frontier, measured as average distance from the VRS (CRS) frontier of those hospitals having TE<1, is as follows: 0.52 (0.52) for small hospitals (<100 beds), 0.69 (0.69) for hospitals with 101-200 beds, 0.80 (0.81) for hospitals with 201-500 beds and 0.86 (0.80) for large hospitals (>500 beds). The average inefficiency increases the smaller the hospitals are. Since we know that being close to the efficient frontier is a signal of capacity saturation, this result implies that large hospitals are working either at full capacity or close to it, while there is spare capacity in small hospitals.

| Beds | Firms | CRS Efficient firms | | VRS Efficient firms | | Firms with IRS | Firms with DRS | Firms with CRS | Avg distance from CRS frontier | Avg distance from VRS frontier |
|---|---|---|---|---|---|---|---|---|---|---|
| | | N | % | N | % | | | | | |
| <100 | 18 | 10 | 56% | 11 | 61% | 4 | 11 | 3 | 0.52 | 0.52 |
| 101-200 | 22 | 10 | 45% | 11 | 50% | 2 | 10 | 10 | 0.69 | 0.69 |
| 201-500 | 23 | 3 | 13% | 7 | 30% | 1 | 5 | 17 | 0.81 | 0.80 |
| >500 | 26 | 7 | 27% | 12 | 46% | 0 | 8 | 18 | 0.80 | 0.86 |

Table 4.5: Summary of efficiency scores 2006 by hospital size

Concerning the returns to scale, in 2006 the largest hospitals exhibit either decreasing returns to scale (8 out of 26), signaling that from a cost perspective they will get lower average costs by decreasing the scale of operation, or constant returns to scale (i.e. they have reached the minimum average costs). The same considerations are valid for the medium–large size hospitals, with a total number of beds between 200 and 500. It is instead interesting to notice that among the small (with less than 100 beds) and the medium-small hospitals, the majority is operating under decreasing returns to scale, signaling that cost savings are possible by reducing their scale of operation. Since there is a political pressure in Italy to keep open small and inefficient hospitals because they are close to patients, we suggest that this should be done together with a reduction in the volume of health services provided by these hospitals.

### 4.5.2 The determinants of efficiency

The second part of the empirical analysis investigates the sources of efficiency differentials among hospitals. The efficiency scores obtained in the previous stage are regressed against a set of exogenous variables which are neither inputs nor outputs, and thus are not under the management's control, but which might influence efficiency, by performing a double–procedure.[11] As shown in table Table 4.1, the exogenous variable I consider relate to ownership, competition, specialization and teaching status.[12]

Table 4.6 displays the result of the second stage analysis. A preliminary remark is necessary to allow the correct interpretation of the coefficients. Given the fact the dependent variable of the truncated regression is bounded by one and infinity, the first meaning full efficiency, the latter inefficiency, an estimated $\beta \geq 0$ means a negative impact on efficiency.

In 1999 public hospitals appear less efficient than private and not–for–profit, while at the end of the period ownership does not influence efficiency. Competitive pressure has a moderate positive impact on efficiency only in 2006. The strongest effect on efficiency is driven by specialization, which shows a negative effect meaning that the larger the width of hospital services provided, the higher the efficiency. This might be due to hospitals' capacity to exploit economies of scope. Furthermore, we observe that this effect rises across the years. Last, teaching status does not have a significant impact on hospitals' efficiency.

| | 1999 | | 2006 | |
|---|---|---|---|---|
| Variable | Coeff | Sign | Coeff | Sign |
| Constant | 1.660 | *** | 1.261 | *** |
| PUBL | 0.251 | *** | 0.023 | |
| CI | -0.320 | | -0.314 | * |
| SI | 0.590 | ** | 2.194 | *** |
| TEACH | -0.129 | | 0.018 | |

Table 4.6: The determinants of efficiency

### 4.5.3 Productivity change

In this section I present the productivity change computed through the Malmquist index. Table 4.7 shows the summary of Malmquist indexes.[13] Between 1999 and 2006 the Total Factor Productivity change is equal to 1.009, i.e. the yearly average increase in hospitals' productivity is equal to

[11] The double–bootstrap code was programmed by Renato Redondi (University of Brescia, Italy) in Matlab.

[12] The dummy variable PUBL is equal to 1 for public hospitals, 0 else; the dummy TEACH is equal to 1 for university hospitals, 0 else.

[13] Appendix 2 shows the productivity change for all the hospitals in the sample between 1999 and 2006.

0.9% and the overall increase during the period is equal to 6.2%. This means that Lombard hospitals have increased their productivity, even if the magnitude of the increase is rather modest.

If we want to explain the source of TFP growth, we can decompose the index into its constituent parts, efficiency change (EC) and technical change (TC), which are linked by the following relationship: $TFPC = EC \times TC$. The first component is equal to 1.010, signaling a slight progress in the relative efficiency from the first to the last period, while the second component is equal to 0.999, meaning that on average the sample has not been able to exploit technology progress. We can further decompose the EC into its components, pure efficiency change (PECH) and scale efficiency change (SECH) which are linked by the following relationship: $EC = PECH \times SECH$. We find an increase both in PECH (1.003) and in SECH (1.007). These results clearly show a growing capacity of the hospitals in the sample to get an better scale of operation and exploit the scale effect.

In summary, we can say that the Malmquist TFP index shows an increasing trend across the period 1999-2006. This overall TFP movement seems to be driven to a large extent by a similar pattern for technical efficiency change, and especially by the scale efficiency change.

| Year | EC | TC | PECH | SECH | TFPCH |
|---|---|---|---|---|---|
| 1999–2000 | 0.984 | 1.02 | 0.970 | 1.014 | 1.004 |
| 2000–2001 | 1.048 | 0.967 | 1.046 | 1.002 | 1.013 |
| 2001–2002 | 1.012 | 1.018 | 1.011 | 1 | 1.03 |
| 2002–2003 | 1.039 | 0.957 | 1.018 | 1.021 | 0.995 |
| 2003–2004 | 0.946 | 1.095 | 0.957 | 0.989 | 1.036 |
| 2004–2005 | 1.024 | 0.958 | 1.029 | 0.995 | 0.982 |
| 2005–2006 | 1.020 | 0.983 | 0.994 | 1.025 | 1.002 |
| Mean | 1.010 | 0.999 | 1.003 | 1.007 | 1.009 |

Table 4.7: Malmquist TFP index: summary of annual means

Figure 4.3 shows the cumulative TFP change from 1999 to 2006. During this period, we can observe an overall increase in the total productivity equal to 6.2%, mainly explainable with the growth of the scale efficiency (+4.6%). Pure technical efficiency exhibits an overall positive change (+2.5%), with the exception of the years 2000 and 2004 as mentioned before. The technical change shows a trend with several large oscillations, and gives an overall slight negative contribution (-0.2%).

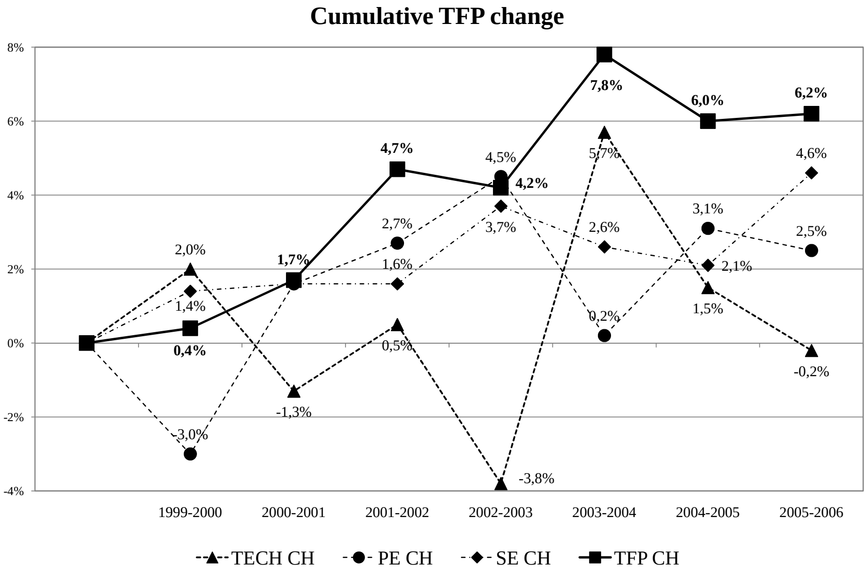


Figure 4.3: Cumulative TFP change 1999–2006

## 4.6 Conclusions

This paper investigates the technical efficiency of the entire population of hospitals active in Lombardy between 1999 and 2006 using the two-stage procedure proposed by Simar and Wilson (2007). In the first stage, I estimate the efficient frontier with Data Envelopment Analysis, while in the second stage the Simar–Wilson double–bootstrap procedure is used to analyze the determinants of efficiency.

My main findings are the following. First, efficiency is positively related to hospitals' size. Hospitals with more than 500 beds are more efficient than the smaller ones. Since a hospital close to the physical efficiency frontier (or on the frontier itself) is heading for saturation in its capacity to offer hospital services, the result implies that large Lombard hospitals are operating at full capacity while small hospitals have spare capacity. Second, large hospitals are mainly working under decreasing returns to scale. On the contrary, increasing returns to scale prevail in hospitals with less than 200 beds. Hence, from a cost perspective, large hospitals should decrease their scale of operation to get a reduction in average costs. As just mentioned, big hospitals are close to capacity saturation. Hence in case of increase of large hospitals' scale of operation, the combination of capacity saturation and decreasing returns to scale, on the one hand, will require further investments (to overcome capacity saturation), on the other hand will lead to higher unit costs (due to decreasing returns to scale). Small hospitals should instead increase their scale of operation in order to get a reduction in average costs (thanks to increasing returns to scale). Third, the truncated regression on the estimated DEA scores shows that efficiency is not influenced by ownership and teaching status. Competition, measured in terms of share of beds per hospital specialty in competition within a ray of 20 km, has a positive impact on hospitals technical efficiency. Specialization, measured by the sum of squares of the share of discharges per specialty, has a strong negative impact on efficiency, meaning that those hospitals which specialize and provide a limited number of services are less efficient. Last, the Malmquist TFP index highlights an increase in the average efficiency in the Italian hospital sector due to a growing capacity of operating at an optimal scale, with a consequent reduction in average costs due to the decrease of the scale of operation.

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## 4.8 References


- Banker, R.D., Charnes, A. and W.W. Cooper, 1984, Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science*, 30, 1078-1092.
- Barbetta, G., Turati, G., 2001, L'analisi dell'efficienza tecnica nel settore della sanit. Un'applicazione al caso della Lombardia, *Economia Pubblica*, 2, 97–127.
- Barbetta, G.P., Turati, G. and A.M. Zago, 2007, Behavioral differences between public and private not–for–profit hospitals in the Italian national health service, *Health economics*, 16, 75–96.
- Byrnes, P., V. Valdmanis, 1994, Analyzing technical and allocative efficiency of hospitals, in A. Charnes, W.W. Cooper, A. Lewin and L.M. Seiford (eds.), *Data Envelopment Analysis: theory, methodology and application*, Boston: Kluwer Academic Publishers, 129–144.
- Burgess, J.F, Wilson, P.W., 1996, Hospital Ownership and Technical Inefficiency, *Management Science* 42, 110–123.
- Cellini, R., Pignataro, G. and I. Rizzo, 2000, Competition and efficiency in health care: an analysis of the Italian case, *International Tax and Public Finance*, 7, 503–519.
- Charnes, A., Cooper, W.W., and E. Rhodes, 1978, Measuring the efficiency of decision making units, *European Journal of Operational Research*, 2, 429–444.
- Coelli T., 1996, A guide to DEAP version 2.1: a data envelopment analysis (computer) program, Armindale, University of New England, CEPA Working Paper no. 96/08.
- Cowing, T.G., Holtmann, A.G., 1983, Multiproduct short-run hospital cost functions: empirical evidence and policy implications from cross-section data, *Southern Economic Journal*, 49, 637–653.
- Chilingerian, J.A., 1994, Exploring why some physicians hospital practices are more efficient: taking DEA inside hospital, in A. Charnes, W.W. Cooper, A. Lewin and L.M. Seiford (eds.), *Data Envelopment Analysis: theory, methodology and application*, Boston: Kluwer Academic Publishers, 167–194.

- Chilingerian, J.A., Sherman, H.D., 1997, DEA and primary care physician report cards: Deriving preferred practice cones from managed care service concepts and operating strategies, *Annals of Operations Research*, 73, 35–66.

- Chilingerian, J.A., Sherman, H.D., 2004, *Health care applications: from hospitals to physicians, from productive efficiency to quality frontiers*, in W.W. Cooper, L.M. Seiford and J. Zhu (eds.), *Handbook on Data Envelopment Analysis*, Kluwer Academic Publishers, 481–537.

- Conrad, R.F., Strauss, R.P., 1983, A multiple–output multiple–input model of the hospital industry in North Carolina, *Applied Economics*, 15, 341–352.

- *Färe*, R., Grosskopf, S. and C.A.K. Lovell, 1994, Production frontiers, New York, Cambridge University Press.

- Farrell, M.J., 1957, The measurement of productive efficiency, *Journal of the Royal Statistical Society, Series A*, 120, 253-290.

- Gerdtham, U.G., Rehnberg, C. and M. Tambourg, 1999, The impact of internal markets on health care efficiency: evidence of health care reform in Sweden, *Applied Economics*, 31: 935–945.

- Grosskopf, S., Valdmanis, V., 1987, Measuring hospital performance: a non parametric approach, *Journal of Health Economics*, 6, 89–107.

- Hersch, P., 1984, Competition and the performance of hospital markets, *Review of Industrial Organization Winter*, 324–341.

- Hollingsworth, B., 1997, A Review of Data Envelopment Analysis Software, *The Economic Journal*, 107, 1268–1270. Hollingsworth, B., P.J. Dawson and N. Maniadakis, 1999, Efficiency measurement of health care: a review of non-parametric methods and applications, *Health Care Management Science*, 2, 161–172.

- Hollingsworth, B., 1999, Data envelopment analysis and productivity analysis: a review of the options, *The Economic Journal*, 109, F458–F462.

- Hollingsworth B., Parkin, D., 2001, The efficiency of the delivery of neonatal care in the UK, *Journal of Public Health Medicine* 23, 47–50.

- Hollingsworth, B., 2003, Non-parametric and parametric applications measuring efficiency in health care, *Health Care Management Science*, 6, 203–218.
- Jacobs, R., 2001, Alternative methods to examine hospital efficiency: Data Envelopment Analysis and Stochastic Frontier Analysis, *Health Care Management Science*, 4, 103–115.
- Jacobs, R., Smith, P.C. , and A. Street, 2006, Measuring efficiency in health care: analytic techniques and health policy, Cambridge University Press.
- Linna, M., 1998, Measuring hospital cost efficiency with panel data models, *Health Economics*, 7, 415–427.
- Lynch, J., Ozcan, Y., 1994, Hospital closure: an efficiency analysis, *Hospital and Health Services Administration* , 39, 205–212.
- Luke, R.D., Ozcan, Y.A., 1995, Local markets and systems: hospital consolidations in metropolitan areas, *Health Services Research*, 30, 555–576.
- Morey, R.C., Fine, D.J. and S.W. Loree, 1990, Comparing the allocative efficiencies of hospitals, *OMEGA International Journal of Management Science*, 18, 71–83.
- ONeill, L., 1998, Multifactor efficiency in Data Envelopment Analysis with an application to urban hospitals, *Health Care Management Science*, 1, 19-27.
- Ozcan, Y.A., Cotter, J.J., 1994, An assessment of efficiency of area agencies on aging in Virginia through data envelopment analysis, *The Gerontologist*, 34, 363–370.
- Ozcan, Y., Lynch, J., 1992, Rural hospital closures: an inquiry into efficiency, *Advances in Health Economics and Health Services Research*, 13, 205–224.
- Puig-Junoy, J., 1998a, Measuring health production in the OECD, *Applied Economics Letters*, 5, 255–259.
- Puig-Junoy, J., 1998b , Technical efficiency in the clinical management of critically ill patients, *Health Economics*, 7, 263–277.

- Puig-Junoy, J., 2000, Partitioning input cost efficiency into its allocative and technical components: an empirical DEA application to hospitals, *Socio-Economic Planning Sciences*, 34, 199–218.

- Robinson, J., Luft, H., 1985, The impact of hospital market structure on patient volume, average length of stay, and the cost of care, *Journal of Health Economics*, 4, 333–56.

- Scott, R.W., 1979, Measuring outputs in hospitals, measuring and interpreting productivity, *National Research Council*, 255–75.

- Shepherd, R.W., 1970, Theory of Cost and Production Functions, Princeton, New York, Princeton University Press.

- Simar, L., Wilson, P.W., 2007, Estimation and inference in two stage, semi–parametric models of productive efficiency, *Journal of Econometrics*, 136, 31-64.

- Simar, L., Wilson, P.W., 1999, Of course we can bootstrap DEA scores! But does it mean anything? Logic trumps wishful thinking, *Journal of Productivity Analysis*, 11, 93-97.

- Street, A., 2003, How much confidence should we place in efficiency estimates?, *Health Economics*, 12, 895–907.

## 4.9 Appendix

### 4.9.1 Appendix 1

| Hospital | CRS TE | VRS TE | SE | RS | Firm | CRS TE | VRS TE | SE | RS |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.893 | 0.916 | 0.975 | irs | 46 | 1 | 1 | 1 | crs |
| 2 | 1 | 1 | 1 | crs | 47 | 0.678 | 0.716 | 0.947 | irs |
| 3 | 1 | 1 | 1 | crs | 48 | 1 | 1 | 1 | crs |
| 4 | 0.616 | 0.84 | 0.734 | drs | 49 | 1 | 1 | 1 | crs |
| 5 | 0.854 | 0.872 | 0.98 | irs | 50 | 1 | 1 | 1 | crs |
| 6 | 0.76 | 0.77 | 0.987 | drs | 51 | 1 | 1 | 1 | crs |
| 7 | 0.565 | 0.706 | 0.8 | drs | 52 | 1 | 1 | 1 | crs |
| 8 | 0.646 | 0.685 | 0.944 | drs | 53 | 1 | 1 | 1 | crs |
| 9 | 1 | 1 | 1 | crs | 54 | 0.482 | 0.484 | 0.995 | drs |
| 10 | 1 | 1 | 1 | crs | 55 | 0.906 | 1 | 0.906 | drs |
| 11 | 0.315 | 0.516 | 0.611 | irs | 56 | 0.221 | 0.231 | 0.955 | irs |
| 12 | 0.357 | 0.375 | 0.951 | drs | 57 | 1 | 1 | 1 | crs |
| 13 | 1 | 1 | 1 | crs | 58 | 1 | 1 | 1 | crs |
| 14 | 0.527 | 0.758 | 0.695 | drs | 59 | 1 | 1 | 1 | crs |
| 15 | 0.2 | 0.205 | 0.974 | irs | 60 | 0.693 | 0.704 | 0.985 | drs |
| 16 | 1 | 1 | 1 | crs | 61 | 0.567 | 0.59 | 0.961 | irs |
| 17 | 0.933 | 1 | 0.933 | irs | 62 | 0.336 | 0.34 | 0.988 | drs |
| 18 | 1 | 1 | 1 | crs | 63 | 0.955 | 1 | 0.955 | drs |
| 19 | 0.573 | 0.726 | 0.789 | drs | 64 | 0.702 | 0.936 | 0.749 | drs |
| 20 | 0.975 | 1 | 0.975 | irs | 65 | 0.624 | 0.698 | 0.894 | drs |
| 21 | 1 | 1 | 1 | crs | 66 | 0.768 | 1 | 0.768 | drs |
| 22 | 0.819 | 0.819 | 0.999 | crs | 67 | 0.644 | 1 | 0.644 | drs |
| 23 | 0.73 | 0.766 | 0.953 | irs | 68 | 0.902 | 0.922 | 0.979 | drs |
| 24 | 1 | 1 | 1 | crs | 69 | 0.71 | 0.912 | 0.779 | drs |
| 25 | 0.877 | 1 | 0.877 | irs | 70 | 0.559 | 0.745 | 0.751 | drs |
| 26 | 0.778 | 0.801 | 0.971 | drs | 71 | 0.952 | 0.957 | 0.994 | drs |
| 27 | 1 | 1 | 1 | crs | 72 | 0.617 | 0.749 | 0.823 | drs |
| 28 | 1 | 1 | 1 | crs | 73 | 0.675 | 0.838 | 0.805 | drs |
| 29 | 0.973 | 1 | 0.973 | drs | 74 | 0.697 | 0.93 | 0.75 | drs |
| 30 | 0.819 | 0.903 | 0.908 | drs | 75 | 0.968 | 1 | 0.968 | drs |
| 31 | 0.694 | 1 | 0.694 | drs | 76 | 1 | 1 | 1 | crs |
| 32 | 0.884 | 0.925 | 0.955 | drs | 77 | 0.755 | 0.958 | 0.789 | drs |
| 33 | 0.658 | 0.662 | 0.994 | drs | 78 | 0.733 | 0.734 | 0.999 | irs |
| 34 | 0.541 | 0.553 | 0.978 | irs | 79 | 0.619 | 0.951 | 0.651 | drs |
| 35 | 0.653 | 0.658 | 0.993 | drs | 80 | 0.865 | 1 | 0.865 | drs |
| 36 | 0.61 | 0.676 | 0.902 | drs | 81 | 0.648 | 0.718 | 0.902 | drs |
| 37 | 0.445 | 0.467 | 0.953 | irs | 82 | 0.788 | 0.799 | 0.986 | drs |
| 38 | 0.895 | 1 | 0.895 | drs | 83 | 0.632 | 0.691 | 0.915 | drs |
| 39 | 1 | 1 | 1 | crs | 84 | 0.599 | 0.633 | 0.947 | drs |
| 40 | 1 | 1 | 1 | crs | 85 | 0.738 | 0.999 | 0.739 | drs |
| 41 | 0.883 | 1 | 0.883 | irs | 86 | 0.569 | 0.78 | 0.73 | drs |
| 42 | 1 | 1 | 1 | crs | 87 | 0.812 | 0.908 | 0.895 | drs |
| 43 | 0.966 | 0.985 | 0.98 | drs | 88 | 0.862 | 1 | 0.862 | drs |
| 44 | 0.541 | 0.544 | 0.995 | irs | 89 | 0.64 | 0.907 | 0.706 | drs |
| 45 | 0.81 | 0.894 | 0.906 | drs | Mean | 0.783 | 0.852 | 0.918 | |

Table 4.8: Results from DEA (1999)

| Hospital | CRS TE | VRS TE | SE | RS | Firm | CRS TE | VRS TE | SE | RS |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.979 | 1 | 0.979 | drs | 46 | 1 | 1 | 1 | crs |
| 2 | 1 | 1 | 1 | crs | 47 | 0.72 | 0.767 | 0.938 | drs |
| 3 | 0.878 | 0.881 | 0.997 | drs | 48 | 0.914 | 0.927 | 0.986 | drs |
| 4 | 0.774 | 0.774 | 1 | crs | 49 | 1 | 1 | 1 | crs |
| 5 | 1 | 1 | 1 | crs | 50 | 1 | 1 | 1 | crs |
| 6 | 0.622 | 0.629 | 0.988 | irs | 51 | 1 | 1 | 1 | crs |
| 7 | 0.573 | 0.591 | 0.969 | irs | 52 | 1 | 1 | 1 | crs |
| 8 | 0.57 | 0.572 | 0.997 | drs | 53 | 0.907 | 0.907 | 1 | crs |
| 9 | 0.856 | 0.888 | 0.964 | drs | 54 | 0.716 | 0.721 | 0.993 | drs |
| 10 | 1 | 1 | 1 | crs | 55 | 1 | 1 | 1 | crs |
| 11 | 0.477 | 0.489 | 0.976 | irs | 56 | 0.334 | 0.356 | 0.938 | drs |
| 12 | 0.688 | 0.758 | 0.908 | drs | 57 | 1 | 1 | 1 | crs |
| 13 | 0.799 | 0.86 | 0.929 | drs | 58 | 0.696 | 1 | 0.696 | drs |
| 14 | 0.841 | 0.85 | 0.989 | drs | 59 | 1 | 1 | 1 | crs |
| 15 | 0.234 | 0.277 | 0.845 | drs | 60 | 0.68 | 0.685 | 0.993 | drs |
| 16 | 1 | 1 | 1 | crs | 61 | 0.445 | 0.45 | 0.991 | drs |
| 17 | 1 | 1 | 1 | crs | 62 | 0.417 | 0.446 | 0.936 | drs |
| 18 | 0.906 | 0.907 | 0.999 | irs | 63 | 0.969 | 1 | 0.969 | drs |
| 19 | 0.81 | 1 | 0.81 | drs | 64 | 1 | 1 | 1 | crs |
| 20 | 1 | 1 | 1 | crs | 65 | 0.721 | 0.766 | 0.942 | drs |
| 21 | 1 | 1 | 1 | crs | 66 | 0.836 | 0.966 | 0.866 | drs |
| 22 | 0.79 | 0.793 | 0.996 | drs | 67 | 0.823 | 1 | 0.823 | drs |
| 23 | 0.627 | 0.633 | 0.99 | drs | 68 | 1 | 1 | 1 | crs |
| 24 | 1 | 1 | 1 | crs | 69 | 0.971 | 1 | 0.971 | drs |
| 25 | 1 | 1 | 1 | crs | 70 | 0.792 | 0.89 | 0.89 | drs |
| 26 | 0.757 | 0.838 | 0.904 | drs | 71 | 0.971 | 0.977 | 0.994 | irs |
| 27 | 1 | 1 | 1 | crs | 72 | 0.726 | 0.797 | 0.911 | drs |
| 28 | 1 | 1 | 1 | crs | 73 | 0.721 | 0.809 | 0.892 | drs |
| 29 | 1 | 1 | 1 | crs | 74 | 0.789 | 0.937 | 0.842 | drs |
| 30 | 1 | 1 | 1 | crs | 75 | 1 | 1 | 1 | crs |
| 31 | 0.901 | 0.919 | 0.98 | drs | 76 | 0.811 | 0.834 | 0.973 | drs |
| 32 | 0.946 | 0.969 | 0.976 | drs | 77 | 0.801 | 0.895 | 0.895 | drs |
| 33 | 0.432 | 0.433 | 1 | crs | 78 | 1 | 1 | 1 | crs |
| 34 | 0.509 | 0.515 | 0.988 | drs | 79 | 0.662 | 0.843 | 0.784 | drs |
| 35 | 1 | 1 | 1 | crs | 80 | 0.817 | 0.818 | 0.999 | drs |
| 36 | 0.946 | 1 | 0.946 | drs | 81 | 0.908 | 0.908 | 1 | crs |
| 37 | 0.681 | 1 | 0.681 | irs | 82 | 1 | 1 | 1 | crs |
| 38 | 0.795 | 0.815 | 0.976 | drs | 83 | 0.8 | 0.83 | 0.964 | drs |
| 39 | 0.358 | 0.365 | 0.981 | irs | 84 | 0.646 | 0.826 | 0.782 | drs |
| 40 | 0.932 | 0.944 | 0.987 | drs | 85 | 0.799 | 0.974 | 0.821 | drs |
| 41 | 1 | 1 | 1 | crs | 86 | 0.709 | 0.749 | 0.947 | drs |
| 42 | 1 | 1 | 1 | crs | 87 | 0.876 | 0.919 | 0.953 | drs |
| 43 | 1 | 1 | 1 | crs | 88 | 0.968 | 1 | 0.968 | drs |
| 44 | 0.394 | 0.448 | 0.881 | drs | 89 | 0.968 | 1 | 0.968 | drs |
| 45 | 0.965 | 1 | 0.965 | drs | Mean | 0.831 | 0.867 | 0.958 | |

Table 4.9: Results from DEA (2006)

### 4.9.2 Appendix 2

| Hospital | TC | PECH | SECH | TFPCH | Hospital | TC | PECH | SECH | TFPCH |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.034 | 1.013 | 1.001 | 1.047 | 46 | 0.968 | 1 | 1 | 0.968 |
| 2 | 0.989 | 1 | 1 | 0.989 | 47 | 0.990 | 1.01 | 0.999 | 0.999 |
| 3 | 1.012 | 0.982 | 1 | 0.993 | 48 | 0.958 | 0.989 | 0.998 | 0.946 |
| 4 | 0.993 | 0.988 | 1.045 | 1.026 | 49 | 0.997 | 1 | 1 | 0.997 |
| 5 | 1.007 | 1.020 | 1.003 | 1.030 | 50 | 1.014 | 1 | 1 | 1.014 |
| 6 | 0.996 | 0.972 | 1 | 0.968 | 51 | 1.013 | 1 | 1 | 1.013 |
| 7 | 0.938 | 0.975 | 1.028 | 0.940 | 52 | 0.981 | 1 | 1 | 0.981 |
| 8 | 1 | 0.975 | 1.008 | 0.982 | 53 | 0.970 | 0.986 | 1 | 0.957 |
| 9 | 0.987 | 0.983 | 0.995 | 0.965 | 54 | 1.003 | 1.058 | 1 | 1.061 |
| 10 | 0.985 | 1 | 1 | 0.985 | 55 | 0.998 | 1 | 1.014 | 1.012 |
| 11 | 0.975 | 0.992 | 1.069 | 1.035 | 56 | 0.963 | 1.064 | 0.998 | 1.022 |
| 12 | 1.012 | 1.106 | 0.993 | 1.111 | 57 | 0.998 | 1 | 1 | 0.998 |
| 13 | 0.884 | 0.979 | 0.990 | 0.857 | 58 | 1.024 | 1 | 0.95 | 0.973 |
| 14 | 0.971 | 1.017 | 1.052 | 1.039 | 59 | 0.992 | 1 | 1 | 0.992 |
| 15 | 0.990 | 1.043 | 0.980 | 1.012 | 60 | 0.999 | 0.996 | 1.001 | 0.996 |
| 16 | 0.996 | 1 | 1 | 0.996 | 61 | 1.013 | 0.962 | 1.004 | 0.979 |
| 17 | 1.153 | 1 | 1.01 | 1.165 | 62 | 1.007 | 1.039 | 0.992 | 1.039 |
| 18 | 1.040 | 0.986 | 1 | 1.026 | 63 | 1.004 | 1 | 1.002 | 1.006 |
| 19 | 0.984 | 1.047 | 1.004 | 1.034 | 64 | 0.996 | 1.009 | 1.042 | 1.048 |
| 20 | 1.014 | 1 | 1.004 | 1.018 | 65 | 0.998 | 1.013 | 1.007 | 1.019 |
| 21 | 1.004 | 1 | 1 | 1.004 | 66 | 1.011 | 0.995 | 1.017 | 1.023 |
| 22 | 1.040 | 0.995 | 1 | 1.035 | 67 | 1.006 | 1 | 1.036 | 1.041 |
| 23 | 1.013 | 0.973 | 1.006 | 0.991 | 68 | 1.005 | 1.012 | 1.003 | 1.020 |
| 24 | 0.964 | 1 | 1 | 0.964 | 69 | 1.001 | 1.013 | 1.032 | 1.047 |
| 25 | 1.097 | 1 | 1.019 | 1.118 | 70 | 1.004 | 1.026 | 1.025 | 1.055 |
| 26 | 0.998 | 1.006 | 0.990 | 0.995 | 71 | 1.011 | 1.003 | 1 | 1.014 |
| 27 | 0.986 | 1 | 1 | 0.986 | 72 | 1.002 | 1.009 | 1.015 | 1.026 |
| 28 | 1.041 | 1 | 1 | 1.041 | 73 | 1.018 | 0.995 | 1.015 | 1.028 |
| 29 | 0.981 | 1 | 1.004 | 0.985 | 74 | 1.012 | 1.001 | 1.017 | 1.030 |
| 30 | 0.998 | 1.015 | 1.014 | 1.027 | 75 | 1.005 | 1 | 1.005 | 1.010 |
| 31 | 0.988 | 0.988 | 1.051 | 1.026 | 76 | 0.985 | 0.974 | 0.996 | 0.956 |
| 32 | 1.016 | 1.007 | 1.003 | 1.026 | 77 | 1.009 | 0.990 | 1.018 | 1.017 |
| 33 | 1.010 | 0.941 | 1.001 | 0.951 | 78 | 1.014 | 1.045 | 1 | 1.060 |
| 34 | 1.005 | 0.990 | 1.001 | 0.996 | 79 | 1.002 | 0.983 | 1.027 | 1.011 |
| 35 | 1.007 | 1.062 | 1.001 | 1.070 | 80 | 1.001 | 0.972 | 1.021 | 0.992 |
| 36 | 1.001 | 1.057 | 1.007 | 1.066 | 81 | 0.995 | 1.034 | 1.015 | 1.044 |
| 37 | 0.985 | 1.115 | 0.953 | 1.046 | 82 | 1.006 | 1.033 | 1.002 | 1.041 |
| 38 | 0.991 | 0.971 | 1.013 | 0.975 | 83 | 0.990 | 1.027 | 1.008 | 1.024 |
| 39 | 0.834 | 0.866 | 0.997 | 0.720 | 84 | 1.005 | 1.039 | 0.973 | 1.016 |
| 40 | 0.984 | 0.992 | 0.998 | 0.974 | 85 | 1.016 | 0.996 | 1.015 | 1.027 |
| 41 | 1.087 | 1 | 1.018 | 1.107 | 86 | 1.003 | 0.994 | 1.038 | 1.035 |
| 42 | 0.958 | 1 | 1 | 0.958 | 87 | 1.013 | 1.002 | 1.009 | 1.024 |
| 43 | 0.992 | 1.002 | 1.003 | 0.997 | 88 | 1.014 | 1 | 1.017 | 1.031 |
| 44 | 0.996 | 0.973 | 0.983 | 0.952 | 89 | 0.995 | 1.014 | 1.046 | 1.056 |
| 45 | 1.004 | 1.016 | 1.009 | 1.029 | Mean | 0.999 | 1.003 | 1.007 | 1.009 |

Table 4.10: Malmquist indexes summary of firm means 1999–2006

# Chapter 5

# How do hospitals respond to Government intervention? Evidence from the cardiac surgery sector

## 5.1 Introduction

In 1995 the Italian Government introduced a new funding mechanism for hospitals operating within the National Health Service, moving from a cost–based reimbursement to a prospective payment system (PPS) based on Diagnosis Related Groups (DRGs). Under the latter, each hospital receives a fixed amount depending on the DRG into which the patient is classified. DRG rates are set at a regional level, since Italian regions have the responsibility for health care organization and administration. This paper investigates the context of Lombard regional health care system. Tariff regulation is one of the financial planning tools adopted by Lombardy. As a matter of fact, Lombard DRG rates are approximately reviewed every year.

This work contributes to a large strain of research which documents hospitals' responses to the introduction of PPS.[1] In particular I refer to those few studies which explored hospitals' reactions to price changes.[2] This paper focuses on the cardiac surgery sector and analyzes percutaneous cardiovascular procedures (henceforth PCPs), a class of operations which showed a large increase during the last decade. According to the principal diagnosis and to the procedures coded in the Hospital Discharge Chart, we can distinguish

[1]For a review of the literature on PPS see Coulam and Gaumer (1991).
[2]See Dafny (2005).

three different kind of PCPs: PCP with acute myocardial infarction (AMI), PCP with coronary artery stent without AMI and PCP without coronary artery stent or AMI. Each kind of PCP is classified into a specific DRG (516, 517 and 518 respectively) and is reimbursed at a specific rate.

Literature highlights that PPS may strongly encourage hospitals to adopt opportunistic behaviours like early discharges, readmissions (Cutler (1995)), patient selection (Ellis (1998), Levaggi and Montefiori (2003)), transfer and sometimes dumping of high cost patients, misclassification and change in the sequence of discharge diagnoses in order to classify patients in higher priced DRGs (Simborg (1981)). Moreover, tariff policy, which often implies raising prices for certain DRGs and decreasing for others, may create further incentive to switch patients from lower–paying to higher–paying DRGs (Silverman and Skinner (2004), Dafny (2005)).

The last aspect will be the subject of the present work. To achieve this goal I analyze all the Lombard hospitals providing PCPs between 2000 and 2007. The two main aims of this study are the following. First, I consider the trend in admission volumes for each DRG concerning PCPs and I investigate whether government interventions have an impact on the growing trend. Second, I study the change over time in the distribution of the patients among the different DRGs and I investigate whether tariff policy creates incentives to switch patients from lower–paying to higher–paying DRGs.

I find evidence that the growth in the number of admissions for higher–paying DRGs is not sensitive either to the increase in DRG rates or to the introduction of policy reforms aiming at reducing the volume of admissions (e.g. budget cap). The trend of admissions for DRG 516, in particular, are significantly explained both by the number of acute myocardial infarctions and by the share of patients aged over 70. On the contrary, the fall in the number of admissions for the lower–paying DRG (i.e. DRG 518) is significantly explained by the reduction in the rates. Last, I find evidence that the introduction of budget cap influenced positively the growing prevalence of admissions for DRG 517 in the PCPs without AMI. Moreover, patients having secondary diseases which worsen their health status are less likely to receive a stent installation.

The paper is organized as follows: in Section 5.2 I describe the procedures subject of the present investigation, in Section 5.3 I describe the institutional setting and the regional government interventions, while in Section 5.4 I present the econometric model. The dataset is reported in Section 5.5, while Section 5.6 presents the econometric results. The main conclusions of the paper are reported in Section 5.7, which ends up the contribution.

## 5.2 Percutaneous cardiovascular procedures trend

This paper focuses on percutaneous cardiovascular procedures (PCPs) and investigates the impact of regional government intervention both on the number of admissions and on the distribution of patients among the three DRGs that identify PCPs. Figure 5.1 highlights an increasing trend in the yearly number of PCPs performed to Lombard patients. The growth appears to be sharp especially for DRG 516 and 517, which represent the two higher–paying DRGs (as will be discussed in the next Section): admissions for DRG 516 rose by 300% in the analyzed period, while DRG 517 grew by 93%. On the contrary, the admissions for the lower–paying DRG (i.e. DRG 518) fell by 52%.

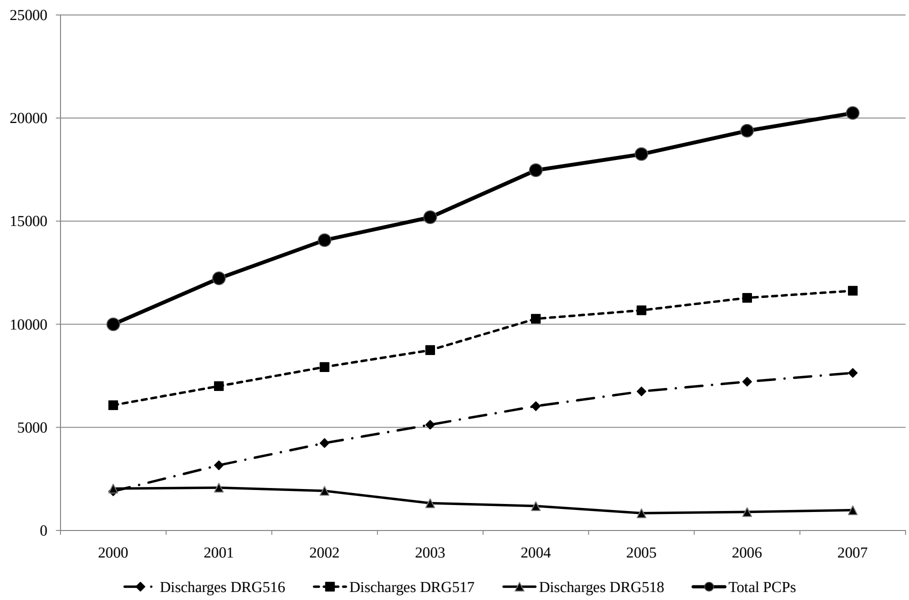


Figure 5.1: Percutaneous cardiovascular procedures' trend

The rise in Lombard population (+6.4% from 2000 to 2007) does not explain the hefty increase in PCPs performed (+102.5%), which turned out in a sharp increase in health expenditure for PCPs (+139.5%). Therefore, the research question of this paper is to investigate whether regional government intervention exerts an impact on this large increase.

## 5.3 Institutional setting

This section presents the Lombard institutional setting and describes the main regional government interventions which might have affected the rise in the number of PCPs performed to Lombard patients between 2000 and 2007, i.e. the change in 2003 in the adopted version of the DRG Grouper, the yearly change in DRG rates and the introduction of budget cap in 2002, suppressed in 2005. The last two ones apply only to Lombard patients. For this reason all the analyses refer to Lombard patients and exclude non–residents.

### 5.3.1 DRG Grouper

Diagnosis Related Groups (DRGs) are a system of classification of inpatient hospital stay on the basis of diagnoses, procedures, age, gender and discharge status. The DRG assignment is made by the DRG Grouper, a computer program which takes the above–mentioned clinical and demographic data as input and gives a corresponding DRG as output. The US federal government's Health Care Finance Administration (HCFA) releases a new DRG version every year since 1982.

Between 2000 and 2007 the Region of Lombardy adopted two different DRG Grouper versions: version 14 between 2000 and 2002, and version 19 since 2003. The $19^{th}$ version of the Grouper introduced some significant changes in the DRGs concerning diseases and disorders of the circulatory system and, in particular, PCPs. While version 14 codifies all the different kind of PCPs into DRG 112 - Percutaneous cardiovascular procedures, version 19 introduces a more detailed classification and distinguishes between PCP with acute myocardial infarction (AMI) (DRG 516), PCP with coronary artery stent without AMI (DRG 517) and PCP without coronary artery stent or AMI (DRG 518).

As shown in Figure 5.2, the introduction of the new classification generated large price increases for DRG 516 and 517, whose admissions represent over 86% of the total amount of PCPs in 2002, and a sharp price decrease for DRG 518.

### 5.3.2 Changes in DRG rates

Since the introduction of the $19^{th}$ version of the Grouper in 2003, the Lombard Region Council has reviewed DRG prices yearly. The following table summarizes the DRG price changes from 2002 till 2006.

In summary, the Lombard DRG tariff policy can be synthesized as follows:

| Decree | Period of validity | Target |
|---|---|---|
| N.11637/2002 | 2003 | Introduction of DRG version 19<br>DRG–specific price changes |
| N.18585/2004 | 2004 | All DRG tariffs increased by 2.1% |
| N.19688/2004 | 2005 | All DRG tariffs increased by 0.881% |
| N.1375/2005 | 2006 | All DRG tariffs increased by 1.5% |
| N.3776/2006 | 2007 | DRG–specific price changes |

Table 5.1: Lombard price changes strategy

1. Price differentiation for PCPs in 2003 following the introduction of the new DRG classification: between 2002 and 2003, DRG 516, which represents PCPs in presence of AMI, increased its tariff by 16%; DRG 517, which identifies PCPs without AMI with stent, increased its tariff by 9%; the least complicated procedures (i.e. PCPs without AMI and without stent), which are classified into DRG 518, decreased their tariff by 17%.

2. Across–the–board adjustment of prices to the cost of living between 2004 and 2006: +2.1% in 2004, +0.881% in 2005 and +1.5% in 2006.

3. Adoption of DRG–specific price changes in 2007 (-2% for DRG 516, -5% for DRG 517 and -2% for DRG 518).

The trend of PCPs' tariffs between 2000 and 2007 is shown in Figure 5.2.

### 5.3.3 Budget cap

In the period analyzed in the present work, we can identify three different strategies in terms of adoption of budget cap for inpatient activity performed for residents, as shown in Table 5.2:

1. In 2000 and 2001 Lombard hospitals were fully reimbursed all the DRGs performed to Lombard patients.

2. In 2002 an upper limit was introduced both to public, private and not–for–profit hospitals revenues. Since then, each hospital is assigned a yearly pre–established budget cap and, in case of overshooting, DRG rates automatically encounter reductions.

3. In 2004 Lombardy published a list of principal diagnoses revealing urgency, which include any AMI initial episode of care. Since 2005 admis-

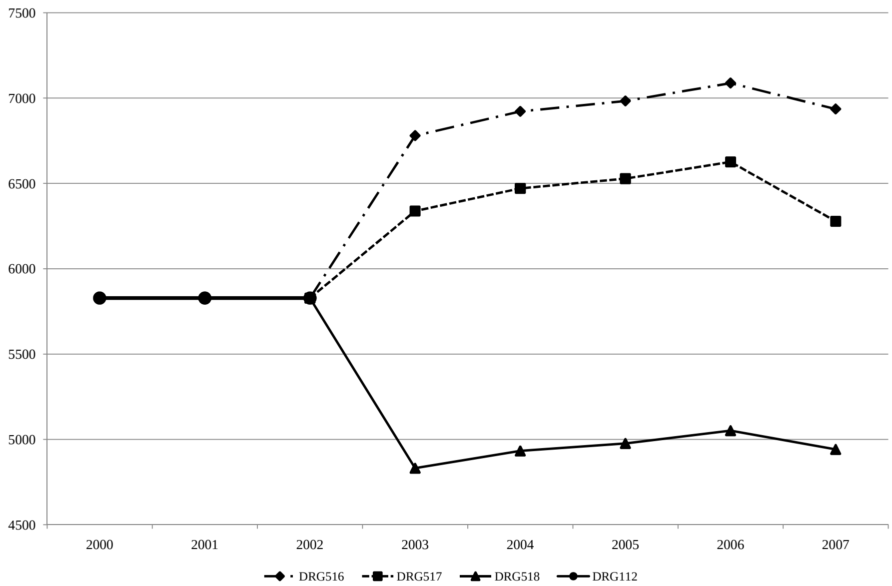


Figure 5.2: Percutaneous cardiovascular procedures' tariffs

sions with principal diagnosis belonging to that list are defined "extra–budget" in the sense they are fully reimbursed any time, without price reductions even though a hospital exceeds the yearly budget cap.

| Decree | Period of validity | Target |
|---|---|---|
| | 2000–2001 | No budget cap |
| N.10807/2002 | 2002–2004 | Introduction of budget cap |
| N.404/2005 | 2005–2007 | Suppression of budget cap for cases with principal diagnosis AMI |

Table 5.2: Lombard budget cap strategy

Table 5.3 summarizes the regional government interventions which might affect the number of admissions for each of the three DRGs analyzed in the present paper.

## 5.4 Methods

The analysis considers all the PCPs performed to Lombard patients during the period 2000–2007. Non–resident patients were excluded since tariff policy and budget cap regulation described in the previous Section are not valid for them.

| | Price changes | Budget cap | Budget cap removal |
|---|---|---|---|
| DRG 516 | X | X | X |
| DRG 517 | X | X | |
| DRG 518 | X | X | |

Table 5.3: Summary of government interventions

As already mentioned, PCPs performed during the period 2000-2002, when DRG Grouper version 14 was adopted, were originally all coded as DRG 112. In order to have homogeneous coding, they were recoded according to the DRG Grouper version 19 codes. Table 5.4 lists the ICD–9–CM codes of diagnosis and procedure which identify PCPs.

| DRG | ICD–9–CM code of procedure | ICD–9–CM code of diagnosis |
|---|---|---|
| 516 | 3601 or 3602 or 3605 or 3606 | 41001 or 41011 or 41021 or 41031 or 41041 or 41051 or 41061 or 41071 or 41081 or 41091 |
| 517 | 3601 or 3602 or 3605 and 3606 | |
| 518 | 3601 or 3602 or 3605 | |

Table 5.4: ICD–9–CM codes identifying PCPs

Once the sample is identified as shown above, I perform two separate analyses according to the government intervention which might influence the number of admissions. In the first part, I consider operations whose trend might be affected by all the government interventions shown in Table 5.3, i.e. PCPs with AMI, represented by DRG 516, while the second part regards those operations which are not affected by the budget cap removal, i.e. PCPs without AMI, identified by DRG 517 and 518.

Following the approach adopted by Dafny (2005),[3] I estimate a Random Effects regression model. Table 5.5 lists the variables used in the regressions. Since both the dependent and the explanatory variables are expressed in logarithms, the first order coefficients are interpretable as elasticities.

[3]Dafny (2005) examines hospital responses to changes in diagnosis–specific prices by exploiting a 1998 reform that generated large prices changes for the DRGs that belong to pair of codes that share the same principal diagnosis and differ only by the age of the patients and the presence or absence of complications. The dependent variable for the analysis is $fraction_{pt}$, the share of admissions to pair $p$ in year $t$ that is assigned to the top code in that pair. The independent variable $spread_{pt}$ is defined as $spread_{pt}$=DRG weight in top code$_{pt}$–DRG weight in bottom code$_{pt}$ and is a measure of upcoding incentive in pair $p$ in year $t$. The author finds that hospitals responded to price changes primarily by upcoding patients to diagnosis codes with the largest price increase.

| Category | Variable | Description |
|---|---|---|
| Dependent variable | $LOGN_{jit}$ | Log of admissions for $DRG_j$; j=516, 517 |
| | $FRAC517_{it}$ | Share of admissions for DRG 517 over DRG 517 + DRG 518 |
| Government intervention | $LOGTAR_{jt}$ | $Log(Rate_{DRG_j,t})$ |
| | $SPREAD_t$ | $Rate_{DRG_H,t}$ - $Rate_{DRG_L,t}$ |
| | $BDG_{jt}$ | 1 in 2002, 2003 and 2004; 0 else, $j$=516 |
| | | 1 from 2002 to 2007; 0 else, $j$=517, 518 |
| | $EXTRA\_BDG_t$ | 1 in 2005, 2006 and 2007; 0 else |
| Patients' characteristic | $LOGAMI_{it}$ | Log of AMI in resident population |
| | $FRAC70_{it}$ | Share of patients aged 70+ |
| | $COMORB_{it}$ | Elixhauser Comorbidity Index |
| Ownership | $PUBL_{it}$ | 1 for public hospitals; 0 else |
| | $NFP_{it}$ | 1 for not–for–profit hospitals; 0 else |
| Time trend | $T$ | $T$=1, ..., 8 |

Table 5.5: The variables used in the regressions

The first set of variables identifies the dependent variables and will be described in detail the next section, all the other variables are the covariates. The second set of variables relates to government interventions occurred in the analyzed period. $LOGTAR_{jt}$ is the $j^{th}$ DRG rate, expressed in logarithm, at time $t$. Given the fact the dependent variable is the logarithm of the performed procedures, $LOGTAR_{jt}$ can be interpreted as price elasticity. $SPREAD_t$ is equal to the difference between the rate of a higher–paying ($DRG_H$) and a lower–paying DRG ($DRG_L$) at time $t$ and measures the incentive to switch patients from $DRG_L$ to $DRG_H$. The next two variables relate to budget cap: $BDG$ is a dummy equal to 1 during the period of adoption of budget cap (i.e. between 2002 and 2004 for DRG 516, and between 2002 and 2007 for DRG 517 and 518), while $EXTRA\_BDG$ captures the impact of the removal of budget cap in the last three years for DRG 516. Furthermore, I use some variables which describe several characteristics of the patients who were installed PCPs in hospital $i$ at time $t$. $LOGAMI_{it}$ is the logarithm of the number of acute myocardial infarctions, $FRAC70_{it}$ is the share of patients aged 70+, while $COMORB_{it}$ is the share of patients having from 1 to 5 comorbidities.[4] Last, I introduce two dummies to control

[4]In medicine comorbidity describes the presence in a patient of other diseases in addition to a primary one. Several indexes have been developed to quantify comorbidity, as Kaplan–Feinstein Index, Charlson Comorbidity Index and Elixhauser Index. In this paper we use the comorbidity measure reported by Elixhauser *et al.* (1998), which the Comorbidity Software, Version 3.3 developed as part of the Healthcare Cost and Utilization Project (HCUP) by the Agency for Healthcare Research and Quality (AHRQ) is based on. Elix-

for possible ownership effects ($PUBL_{it}$ is equal 1 for public hospitals while $NFP_{it}$ is equal to 1 for not–for–profit ones), and time trend which should capture any shift in the technology.

### 5.4.1 Analysis of PCPs with AMI

The dependent variable is $LOGN_{516,it}$, the logarithm of the number of PCPs with AMI (i.e. the admissions for DRG 516) in hospital $i$ at time $t$. In order to examine the effect of government interventions on the number procedures, I estimate the following regression:

$$\begin{aligned} LOGN_{516,it} = \; & \alpha + \beta \Delta LOGTAR_{it} + \gamma BDG_{it} + \delta EXTRA\_BDG_{it} + \\ & + \zeta LOGAMI_{it} + \eta FRAC70_{it} + \theta COMORB_{it} + \\ & + \iota PUBL_{it} + \kappa T + \epsilon_{it} \end{aligned} \tag{5.1}$$

### 5.4.2 Analysis of PCPs without AMI

The second part of the analysis relates to PCPs without AMI, a group of procedures which include a higher–paying DRG (i.e. DRG 517) and a lower–paying DRG (i.e. DRG 518). The analysis is carried out by performing two separate regressions. The first regression aims at investigating whether price changes influence the growth volume of admissions for DRG 517, while the second analyzes whether different changes in DRG rates for DRG 517 and 518 create an incentive to switch patients from the lower–paying to the higher–paying DRG.

In the first regression, the dependent variable is $LOGN_{517,it}$, the log of PCPs without AMI and with stent (i.e. admissions for DRG 517) performed in hospital $i$ at time $t$.

---

hauser *et al.* (1998) identify 30 important comorbidities or conditions present on admission that are not directly related to the main reason of the hospitalization, but that increase the intensity of resources used or increase the likelihood of a poor outcome, i.e. congestive heart failure, cardiac arrhythmias, valvular disease, pulmonary circulation disorders, peripheral vascular disorders, hypertension, paralysis, other neurological disorders, chronic pulmonary disease, uncomplicated diabetes, complicated diabetes, hypothyroidism, renal failure, liver failure, peptic ulcer disease excluding bleeding, AIDS, lymphoma, metastatic cancer, solid tumor without metastasis, rheumatoid arthritis/collagen vascular diseases, coagulopathy, obesity, weight loss, fluid and electrolyte disorders, blood loss anemia, deficiency anemias, alcohol abuse, drug abuse, psychoses and depression. The Elixhauser Index is calculated as the percentage of inpatients having 1–5 secondary diagnosis belonging to the prior list of comorbidities.

$$
\begin{aligned}
LOGN_{517,it} = \quad & \alpha + \beta \Delta TAR_{it} + \gamma BDG_{it} + \delta FRAC70_{it} + \\
& + \zeta COMORB_{it} + \eta PUBL_{it} + \theta T + \epsilon_{it}
\end{aligned} \tag{5.2}
$$

In the second regression, the dependent variable $FRAC_{517,it}$ is the share of admissions for DRG 517 over the total number of PCPs without AMI (i.e. sum of DRG 517 and 518) in hospital $i$ at time $t$.

$$
\begin{aligned}
FRAC_{517,it} = \quad & \alpha + \beta \Delta SPREAD + \gamma BDG_{it} + \delta FRAC70_{it} + \\
& + \zeta COMORB_{it} + \eta PUBL_{it} + \theta T + \epsilon_{it}
\end{aligned} \tag{5.3}
$$

## 5.5 Data

In this paper I investigate the entire population of Lombard hospitals performing PCPs to residents in Lombardy between 2000 and 2007.[5] The main source is represented by the Hospital Discharge Charts Database, which contains a record for each hospitalization, including detailed demographic (age, sex, residence postal code), clinical (diagnoses and procedures) and utilization (lenght of stay) data.

## 5.6 Results

In this Section I present the results of the empirical analysis. To test the robustness of the estimation I perform both a random effects and a fixed effect model. The two results appear to be coherent.

PCPs with AMI (see Table 5.6) show a growing trend over time which seems to be explained mainly by demand characteristics such as the increase in the yearly number of AMI ($\beta = 0.9233$) and in the share of elderly patients ($\beta = 0.8345$).[6] Concerning government intervention, we observe that the number of PCPs increases even during the period 2002–2004, when the Regional Council introduced budget cap as an incentive aimed at lowering the number of admissions, while tariff regulation does not have a significant impact, as well as the hospital ownership form. Several exogenous factors, which might affect the number of procedures performed, are captured by the variable $T$, as the growth in resident population, the change in international

[5]I rule out of the analysis hospitals which treat PCPs only occasionally. The threshold has been fixed at 10 discharges per year following the suggestions of the regional health care officers.

[6]PCPs do not require general anaesthesia, which involves high risks for elderly patients.

guidelines for the treatment of patients affected by AMI and the improvement of the emergency management system. The last aspect is of primary importance given the fact that a timely intervention allows physicians to perform less invasive (and costly) procedure like PCPs instead of bypass surgery.

| | Random Effects | | | Fixed Effects | | |
|---|---|---|---|---|---|---|
| Variable | Coeff | St.Err. | Sign. | Coeff | St.Er. | Sign. |
| LOGTAR | -0.0417 | 0.4230 | | -0.0672 | 0.4251 | |
| BDG | 0.1355 | 0.0695 | * | 0.1489 | 0.0697 | ** |
| E_BDG | 0.0371 | 0.1212 | | 0.0530 | 0.1213 | |
| LOGAMI | 0.9233 | 0.0556 | *** | 0.8659 | 0.0614 | *** |
| FRAC70 | 0.8345 | 0.2468 | *** | 0.8897 | 0.2538 | *** |
| COMORB | 0.0258 | 0.1490 | | -0.0664 | 0.1616 | |
| PUBL | -0.1520 | 0.1730 | | Fixed parameter | | |
| NFP | -0.0519 | 0.2036 | | Fixed parameter | | |
| T | 0.0866 | 0.0256 | *** | 0.0894 | 0.0257 | *** |
| Constant | -0.8594 | 3.6599 | | | | |

Table 5.6: Results for PCPs with AMI (DRG 516)

The following table /5.7) displays the results concerning DRG 517 and highlights that the positive trend in the number of admissions is not significantly explained by government interventions or patients characteristics. Furthermore the trend is significantly rising despite of the introduction of budget cap.

| | Random Effects | | | Fixed Effects | | |
|---|---|---|---|---|---|---|
| Variable | Coeff | St.Err. | Sign. | Coeff | St.Er. | Sign. |
| LOGTAR | -0.0730 | 0.7502 | | -0.0823 | 0.7505 | |
| BDG | 0.2182 | 0.0847 | *** | 0.2222 | 0.0848 | *** |
| FRAC70 | -0.0090 | 0.3388 | | 0.0734 | 0.3417 | |
| COMORB | 0.0468 | 0.1859 | | -0.0176 | 0.1906 | |
| PUBL | -0.1524 | 0.3221 | | Fixed parameter | | |
| NFP | -0.0041 | 0.4218 | | Fixed parameter | | |
| T | 0.0866 | 0.0189 | *** | 0.0867 | 0.0189 | *** |
| Constant | 4.8000 | 6.5082 | | | | |

Table 5.7: Results for PCPs without AMI with stent (DRG 517)

The only procedure whose trend is significantly affected by the reduction in its DRG rate are PCPs without AMI or stent (Table 5.8). Moreover, the coefficient of the variable which relates to comorbidities tells us that patients in worse health status are less likely to be installed a PCP.

| | Random Effects | | | Fixed Effects | | |
|---|---|---|---|---|---|---|
| Variable | Coeff | St.Err. | Sign. | Coeff | St.Er. | Sign. |
| LOGTAR | 2.2568 | 0.6994 | *** | 2.3401 | 0.7002 | *** |
| BDG | 0.1557 | 0.1250 | | 0.1659 | 0.1252 | |
| FRAC70 | 0.2502 | 0.2022 | | 0.3353 | 0.2064 | |
| COMORB | -0.3513 | 0.1845 | * | -0.4667 | 0.1909 | ** |
| PUBL | -0.3963 | 0.3031 | | Fixed parameter | | |
| NFP | -0.3351 | 0.4013 | | Fixed parameter | | |
| T | -0.0846 | 0.0256 | *** | -0.0810 | 0.0258 | *** |
| Constant | -15.9899 | 6.0767 | *** | | | |

Table 5.8: Results for PCPs without AMI or stent (DRG 518)

The last regression I performed aims at investigating whether government intervention creates incentives to switch patients from DRG 518 (i.e. the lower–paying procedure) to DRG 517 (the higher–paying one). Table 5.9 shows a slight increase in the prevalence of DRG 517, and mainly in public and not–for–profit hospitals, while patients having comorbidities are less likely to be installed a stent. The change in DRG rates is insignificant due to the approximately null magnitude of its coefficient ($\beta = 0.00004$), while the share of DRG 517 is significantly higher after the introduction of budget cap in 2002.

| | Random Effects | | | Fixed Effects | | |
|---|---|---|---|---|---|---|
| Variable | Coeff | St.Err. | Sign. | Coeff | St.Er. | Sign. |
| SPREAD | 0.0000 | 0.0001 | *** | 0.0000 | 0.0000 | *** |
| BDG | 0.0289 | 0.0153 | * | 0.0268 | 0.0154 | * |
| FRAC70 | 0.0371 | 0.0533 | | 0.0609 | 0.0604 | |
| COMORB | -0.0427 | 0.0246 | * | -0.0309 | 0.0337 | |
| PUBL | 0.0287 | 0.0141 | ** | Fixed parameter | | |
| NFP | 0.0423 | 0.0186 | ** | Fixed parameter | | |
| T | 0.0099 | 0.0033 | *** | 0.0094 | 0.0033 | *** |
| Constant | 0.7320 | 0.0257 | *** | | | |

Table 5.9: Results for share of DRG 517 over PCPs without AMI

## 5.7 Conclusions

This paper investigates how hospitals respond to government intervention such as tariff regulation and the adoption of budget cap. I analyze the entire population of Lombard hospitals which performed percutaneous cardiovascular procedures to resident patients between 2000 and 2007.

I find evidence that hospitals' decisions seem to be mainly guided by the growth in the number of acute myocardial infarctions and by patients' characteristics such as the share of elderly and the presence of comorbidities which worsen the health status. On the contrary, tariff regulation does a explain significantly the trend. The adoption of strategies aiming at reducing the overall volume of admissions (e.g. budget cap) did not produce the expected goal in terms of containment of number of PCPs provided. On the contrary, it positively influenced the shift of patients from lower–paying to higher–paying DRGs.

Further research is needed on studying thoroughly the evolution of the international guidelines, the improvement of the emergency management system (in terms of number of number of hospitals accredited for performing cardiac surgery and interventional cardiology, number of ambulances, average waiting time from the call for help to the intervention) and the measured effectiveness of PCPs.

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## 5.9 References


- Coulam, R.F., Gaumer, G.L., 1991, Medicare's prospective payment system: a critical appraisal, *Health Care Financing Review*, 13, 45–77.

- Cutler, D.M., 1995, The incidence of adverse medical outcomes under prospective payment, *Econometrica*, 63, 29–50.

- Dafny, L.S., 2005, How do hospitals respond to price changes?, *American Economic Review*, 95, 1525–1547.

- Elixhauser, A., Steiner, C., Harris, D.R., and Coffey, R.M., 1998, Comorbidity Measures for Use with Administrative Data, *Medical Care*, 36, 8–27.

- Ellis, R.P., 1998, Creaming, skimping and dumping: provider competition on the intensive and extensive margins, *Journal of Health Economics*, 17, 537-555.

- Levaggi, R. and Montefiori, M., 2003, Horizontal and vertical cream skimming in the health care market, *DISEFIN Working Paper No. 11/2003*, Available at SSRN: http://ssrn.com/abstract=545583

- Silverman, E., Skinner, J., 2004, Medicare upcoding and hospital ownership, *Journal of Health Economics*, 23, 369–389.

- Simborg, D.W., 1981, DRG creep: a new hospital–acquired disease, *The New England Journal of Medicine*, 304(26), 1602–1604.