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The temporal variation of cost-efficiency in Switzerland's hospitals: an application of mixed models

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Abstract This paper uses a mixed effects model to examine the temporal variation of cost efficiency in Switzerland's general hospitals. The variations in total costs, the number of empty beds and the length of hospital stays are analyzed using financial data from a sample of 168 hospitals operating from 1998 to 2003, as well as hospitalization records disaggregated to Diagnosis Related Groups. Individual intercepts and random coefficients are used to account for the unobserved time-invariant heterogeneity and the differences in temporal patterns across hospitals and DRG categories. The analysis illustrates the usefulness of mixed models to account for unobserved factors such as quality, with a relatively weak assumption that their temporal variations, rather than their initial levels, be uncorrelated with efficiency changes. The results indicate that hospitals have adopted measures to curtail hospitalizations and reduce empty beds. The extent and effectiveness of these measures vary significantly across individual hospitals. However, there is no evidence in favor of a particular ownership type or subsidization regime. While the link between reduction rates of empty beds and gains in cost-efficiency is statistically significant, the expected association between shortening hospital stays and cost-efficiency cannot be clearly established in the data.

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1 Introduction

The increasing growth of health care costs in Switzerland has raised public concern for containing the hospitalization costs. Starting from 1994, together with the introduction of the mandatory federal insurance law and its implementation in 1996, the Swiss legislators have provided the cantonal authorities with several discretionary measures to control hospitals' operating costs. Among these measures was the gradual implementation of a prospective reimbursement system based on Diagnosis Related Groups (DRG).[1]

Thus far, the implementation of DRG-based payment system has been mainly limited to specific services such as ambulatory visits and over-night hospitalizations. Aware of the ongoing reforms, hospital managers are increasingly engaged in the economical planning of their hospitalizations. In particular, the mandatory DRG coding requirement for all hospitalizations introduced in 1998 can be considered as a preface to cost saving pressures. Policy debates reflect a

[1] DRG is a system of classification based on the required hospital resources. DRG codes are assigned by patented computer programs using information on diagnoses, complications/comorbidities and procedures as well as patient's age and gender. DRGs have been first used by Medicare (the US health insurance program for the elderly) in its case-based reimbursement rules, known as Prospective Payment System. Hospitalization costs of each DRG are usually estimated by statistical analysis of large samples of similar cases. In Switzerland, this information is provided by 'APDRG Suisse,' a non-profit association comprising of DRG users throughout the country.

common perception that certain types of hospitals do not have strong incentive for a substantial improvement in their efficiency. Small local hospitals, non-profit providers and university hospitals have often been singled out as inefficient providers.

Several studies tried to detect the efficiency differences across different ownership and organization types (cf. Farsi and Filippini 2006, 2008; Steinmann and Zweifel 2003). The main difficulty of such analyses is that the efficiency differences among hospital types might be biased by the potential cost effects of unobserved exogenous factors. However, the required simplifying assumption that the unobserved heterogeneity is uncorrelated with efficiency differences, has received little attention. This assumption is particularly debatable if important factors such as quality and/or case mix are not completely observed.

In this paper focusing on growth rates instead of levels of efficiency, I get around the problem of unobserved heterogeneity to the extent that the temporal variation of omitted variables is uncorrelated with efficiency changes. This is a relatively weak assumption in that it allows correlation between heterogeneity and initial values of efficiency. Assuming that the hospitals have undertaken cost-saving measures, I use a mixed effects model to estimate the evolution of cost-efficiency over the "reform period" starting from 1998. Rather than searching for a reliable estimate of a specific hospital's efficiency at a given period, the focus is upon hospital-specific rates of change in cost-efficiency and their differences across hospital types. Moreover, I analyze the relationship of efficiency changes with observed decreases in empty beds and length of stays. Such analyses can provide some insight on the overall effectiveness of the cost-saving measures adopted by the hospitals and their eventual impact on quality of service.

The data are based on a relatively rich panel of 168 general hospitals operating from 1998 to 2003 and about 108,000 records of the average length of hospitalization of patients with similar DRG's. The econometric specification is based on a special version of the general parametric framework proposed by Sickles (2005), or the mixed effects model proposed by Kneip et al. (2003), combining individual hospital and DRG fixed effects with random coefficients of the time variables. The adopted model can also be considered as an extension of the random effects model proposed by Cornwell et al. (1990).

While pointing to significant efficiency differences among hospitals regarding their cost-reduction efforts, the results do not provide any evidence in favor of a particular hospital ownership type or subsidization status. The analysis in general indicates that hospitals with relatively important cuts in their empty beds are likely to have relatively high efficiency gains. The evidence regarding the hospitalization length is not conclusive. In most cases, the cost reductions often expected from shortening hospital stays do not appear to be significant.

The rest of the paper is organized as follows. Section 2 provides a critical discussion of the methods of efficiency estimation and justifies the adopted methodology used in this paper. The econometric specification and the explanatory variables are described in Section 3. Section 4 summarizes the data and provides the descriptive statistics of the main variables included in the models. Section 5 presents and analyzes the estimation results and Section 6 concludes the paper with summary of main results and policy implications.

2 Methods

The estimation of firm-specific efficiency is a contentious topic that has been subject of a great body of literature with a variety of econometric models commonly referred to as Stochastic Frontier Analysis. The application of these models to hospitals has been questioned by several authors (Newhouse 1994; Skinner 1994; Street 2003; Folland and Hofler 2001). The main criticism lies on the aggregation of a myriad of services provided by a hospital into a few output measures, required by any practically manageable multi-output cost function.

Despite these general criticisms the efficiency analysis in health care sector remains commonplace (Hollingsworth and Street 2006; Worthington 2004; Jacobs et al. 2006). While admitting the limitations of their approach many authors have adopted various measures for accounting for output characteristics such as case mix severity indexes and other distinctive hospital characteristics (Zuckerman et al. 1994; Linna 1998; Rosko 2001; Deily and McKay 2006; Brown 2003). Other studies have used econometric modeling strategies that have proved more robust in presence of such heterogeneities (Liu et al. 2007; Bradford et al. 2001) or panel data models that account for unobserved factors through hospital-specific stochastic terms (Farsi and Filippini 2008).

The frontier literature is especially rich in panel data modeling approaches with a variety of underlying assumptions about temporal variations of efficiency. While models such as Kumbhakar (1990) and Battese and Coelli (1992) assume a uniform variation for all the firms, others such as Kumbhakar (1991), Polachek and Yoon (1996) and more recently Greene (2005) allow for stochastic variation without any correlation over time. The latter models include three stochastic components respectively for efficiency, random noise and time-invariant heterogeneity.

While recognizing that the firm's efficiency can considerably change over time, a fully stochastic variation over time implies an idiosyncratic nature for the temporal changes. This is probably a too flexible assumption that ignores the fact that efficiency changes are driven by an underlying learning process specific to the firm's management and their efforts. As Alvarez and Schmidt (2006) point out, even though the randomness appears to be quite important, 'over longer periods of time, skill persists while luck averages away.' Even assuming that firms constantly face new technology shocks and market developments that make their resulting productive efficiency look like a stochastic variable, an independent identical time distribution is unrealistic.

As Sickles (2005) points out, in many cases the parametric assumptions help to have a better interpretation of the results. Therefore, a reasonable assumption would be to assign a deterministic functional form for the temporal variation of firm's efficiency while allowing for changes in the values of the parameters across individual companies. This is the approach adopted by Cornwell et al. (1990) through a quadratic function and Lee and Schmidt (1993) with a linear function both with random coefficients that vary across firms. The functional form and the variation of the individual effects have been later extended to mixed effects models and semi-parametric models respectively by Kneip et al. (2003) and Sickles (2005). These models reconcile the idea of heterogeneity with the need for imposing a time structure upon efficiency changes.

Sickles (2005) provides a general framework for the treatment of time-varying efficiency. He recognizes the vulnerability of efficiency and productivity measures as estimation residuals and 'reduced form' concepts that are inevitably based on ad hoc econometric specifications. With a series of Monte Carlo simulations and applying several alternative specifications, the author highlights the difficulties in identifying firm-specific and time-varying efficiency. Sickles (2005) asserts that the robustness, flexibility and precision are the most 'important distinguishing features' that should be considered in model specification strategies.

Lack of robustness can be due the reliance of many frontier models on non-testable distribution assumptions often required to distinguish random noise from the efficiency term. For instance, the original frontier approach in cross-sectional data (Aigner et al. 1977; Meeusen et al. 1977) assigns a half-normal distribution to efficiency and a normal distribution to random noise. This model as well as many later extensions relies upon skewed residuals to produce any meaningful values for efficiency estimates. In many cases, one of the stochastic components might easily degenerate to zero because of a misspecification of the explanatory variables. This sensitivity can be exacerbated in panel data models that decompose the residuals into three components instead of two.

Robustness can be achieved by relaxing the assumptions on the distribution and correlation structures, usually at a loss of precision or identification. For instance, considering freely distributed fixed effects instead of random effects allows more realistic assumptions about the potential correlation between the individual effects and the explanatory variables. However the fixed effects capture the unobserved time-invariant factors, which if correlated with efficiency, distort the pattern of efficiency differences among the companies. In these cases, the potential estimation bias in the overall efficiency can be anticipated depending on the model.[2] However, assessing the resulting biases for individual companies is a matter of pure speculation. Therefore, using fixed effects requires an assumption about the correlation of individual effects not with explanatory variables, but with efficiency differences.

In this paper, recognizing that time-invariant differences in efficiency are captured by the fixed effects, thus indistinguishable from the remaining unobserved heterogeneity, the fixed effects are used to ensure an unbiased estimation of temporal changes in efficiency to the extent that they are uncorrelated with temporal changes in other unobserved factors. Therefore, the proposed model combines a fixed effects approach for intercepts with random effects for time variables representing various temporal patterns across individuals.[3] A formal description of this specification will be presented in the next section.

Another important issue in the estimation of productive efficiency is the study of the sources of inefficiency. The reduced form of the frontier model does not allow in itself an understanding of the inefficiency sources. As Sickles (2005) elegantly points out, a 'strong institutional understanding of the industry under study' is required to choose an adequate estimator among the available alternatives that satisfy the generic properties. Given the existing discrepancy and sensitivity issues in the frontier methodology (as discussed earlier), most studies face a recurrent question regarding the validity and reliability of efficiency estimates, namely, whether these estimates are artifact of

[2] The overall inefficiency is usually over-stated should the fixed effects be interpreted as inefficiency as in Schmidt and Sickles (1984), and understated if they are considered as external factors unrelated to cost-efficiency as in Polachek and Yoon (1996) and Greene (2005). Farsi and Filippini (2004) show how the efficiency differences could reach implausible levels in the former case. As for the latter cases, where inefficiency is identified as an additional skewed stochastic term, this author's experience suggests that the available algorithms have a high risk of producing unreliable estimates of the fixed effects. Farsi et al. (2005) propose a solution around the incidental parameters problem by combining Mundlak's (1978) specification to Greene's (2005) random effects model.

[3] Sickles' (2005) general framework can be applied with fixed effects for temporal changes as well, however at a considerable loss of the model's degrees of freedom. For instance in a quadratic form for temporal variations would require 3 fixed parameters for each hospital, which might create a plausibility problem for short and medium panels.

sampling variations. A common approach is to explore the statistical association between efficiency estimates and the potential sources of inefficiency or to directly integrate such relationships into the frontier model. This approach is however plagued by the possible correlations with third-party unobserved factors such as quality that could bias the results. I argue that the effects of such correlations are attenuated when the relationships are explored between the growth/reduction rates instead of levels. In fact, focusing on temporal changes allows us to reduce the heterogeneity bias due to correlation with time-invariant factors.

For instance, unnecessarily long hospitalizations might be a source of excess costs. This is surely a debatable issue that has been subject of a number of papers. For instance Carey (2000) provides evidence that the US hospitals, facing the policy concerns about rising costs, have reduced the lengths of hospitalizations. Her findings suggest however, that the extent of cost savings has been commonly overstated. Other studies suggested that curtailing the hospital stays has led to a deterioration of quality of care and might have a counter-productive effect in the long run. In Switzerland, there is a considerable variation in the average length of stay (LOS) among hospitals with the small local hospitals having significantly longer hospitalizations, suggesting possible inefficiencies (Farsi and Filippini 2006). Another potential source of inefficiency in hospitals could be related to excess capacity. For instance Gaynor and Anderson (1995) estimate that in the US, the costs of empty hospital beds could amount to 9.5% of the total costs.

Partial efficiency measures based on changes in length of hospital stays and the number of empty beds could be helpful in understanding how the hospitals have dealt with those possible sources of inefficiency. In particular, measures based on LOS are less affected by aggregation bias for, unlike cost data, the records of hospital stays are generally available for individual patients. In this paper, in addition to hospital costs, I use the average LOS at the DRG level and average number of hospital's empty beds. The statistical relationships between these measures are used to assess the differences in cost-cutting strategies across various hospital types.

3 Model specification

The measure of hospital's cost efficiency is based on a total cost function with a Cobb-Douglas functional form.[4] The two complementary measures are the excess capacity defined by the hospital's average number of empty beds and a measure of hospital's excessive LOS based on the average length of hospitalization. The working hypothesis is that the hospitals have adopted measures to contain their operating costs by improving their overall productive efficiency, by reducing their excess capacity, or by curtailing the hospital stays. Including individual fixed effects allows a straightforward identification of the temporal variation of each of the three variables without worrying about the unobserved hospital's time-invariant characteristics[5] and their potential correlation with the observed explanatory variables.

The downside is that those efficiency differences across hospitals that are stable over time are entirely captured by the fixed effects, thus inseparable from other time-invariant external heterogeneities. Therefore, any assessment of the hospitals' efficiency in a given year (relative to other hospitals), is valid only to the extent that the hospitals do not differ significantly with respect to their initial efficiency before the reforms say in 1998. However, it should be noted that the analysis in this paper and the policy conclusions reported here, are strictly based on the temporal changes of efficiency, thus do not require any assumption on efficiency levels. Rather, the required assumption here is that the efficiency gains or losses be uncorrelated with the temporal changes of other unobserved factors such as hospital quality.

The explanatory variables for the cost function include two outputs namely, a DRG-adjusted number of hospitalizations, a measure of ambulatory services offered by the hospital, and three input factor prices i.e., labor price in two categories, non-physician employees and employed physicians, and capital price. The average LOS and the number of medical training positions (interns and medical students) have also been included as output characteristics. For the excess capacity the explanatory variables are specified as follows: the number of hospitalizations and the share of patients with private health insurance. The idea here is that hospitals should adjust the number of available beds

[4] The adopted cost function is similar to the specification used in Farsi and Filippini (2008), with the difference that here because of the presence of individual fixed effects, a number of variables that are time-invariant or practically stable over time are excluded. Similarly, the choice of Cobb–Douglas from as opposed to flexible forms such as translog is motivated by the trade-off between flexibility and the model's degrees of freedom, especially restricted here because of fixed effects. Moreover, we do not impose the restriction of linear homogeneity in input prices, because as we see later in the data section, the included input prices do not cover all the input factors.

[5] These omitted characteristics could include hospital's specialization level, quality of service, and also case mix severity to the extent that these factors depend on hospital location and long-term factors such as medical staff and reputation. Concerning the case mix it should be noted that the DRG adjustment (used in the specification) is only an imperfect measure of severity, thus the within-DRG variations across hospitals remain unobserved.

according to the fluctuations in the demand and also to accommodate the patients entitled to private rooms.

The analysis of hospitalization lengths has been conducted at the DRG level. Namely, the dependent variable is the average LOS for the patients within a given DRG hospitalized in a given hospital-year. Individual fixed effects are considered for each hospital-DRG group. In addition to time variables, the total number of training positions has been included as explanatory variable. The findings in previous studies such as Rogowski and Newhouse (1992) and Simmer et al. (1991) suggest that hospitals with more teaching activities are likely to have longer hospitalizations.[6] As shown by Martin and Smith (1996), the length of stay could depend on several patient characteristics that cannot be summarized in the DRG categories, thus remain among unobserved variables in the present analysis. Part of such variations should be captured by the hospital-DRG fixed effects.

The definition and the summary statistics of all the variables included in the models will be provided in the data section. Now we turn to the econometric specification: The cost model is based on a mixed effects model written as:

$$\ln C_{it} = \boldsymbol{\beta} \ln \mathbf{X}_{it} + \gamma \mathbf{Z}_i + \rho t + \varphi t^2 + \alpha_i + u_{it} + \varepsilon_{it}, \qquad (1)$$

where i and t represent the hospital and year respectively with $t = 0$ representing the first year covered in the sample; C is the total costs; $\ln\mathbf{X}_{it}$ is the vector of time-varying explanatory variables expressed in logarithm; $\mathbf{Z}_i$ is a vector including all the hospital-specific characteristics that do not vary with time; and $[\boldsymbol{\beta}, \boldsymbol{\gamma}, \rho, \varphi]$ is the vector of regression coefficients. The stochastic terms α_i and ε_{it} respectively represent the hospital's individual effect and the random noise. Finally u_{it} is the inefficiency (here excess costs) of hospital i at year t, specified as a quadratic function of time:

$$u_{it} = u_{i0} + \delta_i t + \theta_i t^2, \qquad (2)$$

with u_{i0} representing hospital i's initial inefficiency at year $t = 0$, δ_i and θ_i are random coefficients with a multivariate normal distribution, specified as:

$$\begin{pmatrix} \delta_i \\ \theta_i \end{pmatrix} \sim N(\mathbf{0}, \boldsymbol{\Sigma}); \text{ with } \boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix}, \qquad (3)$$

where $(\sigma_1, \sigma_2, \sigma_{12})$ are the parameters to be estimated. The residual term ε_{it} is assumed to be normally distributed with zero mean: $N(0, \sigma_\varepsilon^2)$ and the individual effects α_i are assumed to be constant fixed effects.

The mean values of the random coefficients (δ_i, θ_i) have been set to zero. This is a simplifying assumption that allows the parameters (ρ, φ) to be identified, while recognizing that the hospital costs might follow a growth pattern that is not related to hospitals' efficiency, but due to external factors, such as the general progress in medical treatments and pharmaceuticals that are increasingly more costly. Such temporal variations that are not captured by the explanatory variables included in the model, are assumed to be more or less similar for all hospitals, thus represented by the average growth in costs captured by parameter pair (ρ, φ).

Noting that because of the presence of the fixed effects the coefficient vector $\boldsymbol{\gamma}$ cannot be identified, the model in Eqs. 1 and 2 can be easily transformed to a random-coefficient model on the deviations from hospital mean, written as:

$$\begin{aligned} \Delta_i \ln C_{it} = & \boldsymbol{\beta} \cdot \Delta_i \ln \mathbf{X}_{it} + \rho \cdot \Delta_i t + \varphi \cdot \Delta_i t^2 + \delta_i \cdot \Delta_i t \\ & + \theta_i \cdot \Delta_i t^2 + \varepsilon_{it}, \end{aligned} \qquad (4)$$

where $\Delta_i x_{it}$ for a generic variable x_{it} is defined as the deviation of the variable from its mean value $(\bar{x}_i)$ within hospital i:

$$\Delta_i x_{it} = x_{it} - \bar{x}_i\,; \text{ with } \bar{x}_i = \frac{1}{T_i} \sum_{t=0}^{T_i} x_{it}, \qquad (5)$$

and T_i is the number of periods for hospital i.

As it can be seen the above specification does not allow a separate identification of the unobserved heterogeneity represented by fixed effects α_i and the initial inefficiencies denoted by u_{i0}. Both of these terms along with the time-invariant variables $\mathbf{Z}_i$ (including the intercept) are canceled out in the within transformation. It is important to highlight that while being useful for an effective estimation of the temporal variations free from time-invariant heterogeneity, the fixed effects capture all the 'between' variation, namely the long-term and persistent differences across hospitals. Therefore, the marginal effects and elasticities estimated from this model are strictly driven from within-hospital variations that are generally of a transient short-term nature. The implication is that the estimated results can only be used to predict quantities or behaviors that entail a limited range of variation comparable to the within-hospital variations in the sample. This caveat is particularly important for technological characteristics of the production function such as returns to scale, that are best identified through long-term differences between hospitals with different scales of production.

The model used for the analysis of the hospitals' excess capacity is similar to that described in Eq. 4 with the difference that the dependent variable is the number of hospital's empty beds (instead of total costs) and includes its own the explanatory variables **X**. Another difference is that unlike costs, there is no reason other than efficiency improvement that the excess capacity should uniformly

[6] In line with the Rogowski and Newhouse, we assume that this effect is a result of 'indirect' costs of training medical students rather than hospital's inefficiency suggested by Simmer et al. (1991).

grow or decrease among all hospitals. Therefore it is reasonable to relax the zero-mean assumption for the individual random coefficients. Thus, the resulting specification can be written as:

$$\Delta_i \ln E_{it} = \boldsymbol{\beta}^e \cdot \Delta_i \ln \mathbf{X}_{it} + \delta_i^e \cdot \Delta_i t + \theta_i^e \cdot \Delta_i t^2 + \varepsilon_{it}^e, \quad (6)$$

where E is the number of empty beds and superscript e denotes parameters related to excess capacity; and the random coefficients are specified as:

$$\begin{pmatrix} \delta_i^e \\ \theta_i^e \end{pmatrix} \sim N(\boldsymbol{\mu}^e, \boldsymbol{\Sigma}^e); \text{ with } \boldsymbol{\mu}^e = \begin{pmatrix} \rho^e \\ \varphi^e \end{pmatrix}, \boldsymbol{\Sigma}^e = \begin{pmatrix} (\sigma_1^e)^2 & \sigma_{12}^e \\ \sigma_{12}^e & (\sigma_2^e)^2 \end{pmatrix}. \quad (7)$$

The analysis of hospitals' average length of stay (LOS) has been conducted at DRG level observations. Denoting DRG group by subscript j, the model specification for this analysis can be formulated as:

$$\Delta_{ij} \ln L_{ijt} = \boldsymbol{\beta}^l \cdot \Delta_{ij} \ln \mathbf{X}_{ijt} + \delta_{ij}^l \cdot \Delta_{ij} t + \theta_{ij}^l \cdot \Delta_{ij} t^2 + \varepsilon_{ijt}^l, \quad (8)$$

where L_{ijt} is the average LOS for DRG group j hospitalized in hospital i during period t; superscript l denotes parameters related to LOS equation; and the random coefficients and the within operator are respectively defined as:

$$\begin{pmatrix} \delta_{ij}^l \\ \theta_{ij}^l \end{pmatrix} \sim N(\boldsymbol{\mu}^l, \boldsymbol{\Sigma}^l); \text{ with } \boldsymbol{\mu}^l = \begin{pmatrix} \rho^l \\ \varphi^l \end{pmatrix}, \boldsymbol{\Sigma}^l = \begin{pmatrix} (\sigma_1^l)^2 & \sigma_{12}^l \\ \sigma_{12}^l & (\sigma_2^l)^2 \end{pmatrix}, \quad (9)$$

$$\Delta_{ij} x_{ijt} = x_{ijt} - \bar{x}_{ij}\,; \text{ with } \bar{x}_{ij} = \frac{1}{T_{ij}} \sum_{t=0}^{T_{ij}} x_{ijt}, \quad (10)$$

where T_{ij} is the number of periods for patients with DRG j treated in hospital i.

The random-coefficient models described in Eqs. 4, 6 and 8 will be estimated using the EM algorithm. Based on the estimated parameters and the obtained residuals for each hospital, the hospital specific parameters are calculated using a conditional Bayesian predictor denoted hereafter, by a superposed symbol ^. The changes in *excess*[7] *costs*, *capacity* and *LOS* for a given hospital i as well as the sector's growth in total costs due to technological progress can therefore be identified compared to the beginning of the sample period (1998). These temporal changes are respectively specified as:

$$\begin{aligned} \text{Excess Costs: } \Delta u_i &= \hat{\delta}_i t + \hat{\theta}_i t^2 \\ \text{Excess Capacity: } \Delta u_i^e &= \hat{\delta}_i^e t + \hat{\theta}_i^e t^2 \\ \text{Excess LOS: } \Delta u_i^l &= \hat{\delta}_i^l t + \hat{\theta}_i^l t^2 \\ \text{Sector's Cost Trend: } \Delta c &= \hat{\rho} t + \hat{\phi} t^2 \end{aligned} \quad (11)$$

In order to test the statistical significance of efficiency differences across different ownership/subsidy types, I apply the Kruskal and Wallis (1952) rank test to the predicted random coefficients $\delta_i, \theta_i, \delta_i^e, \theta_i^e, \delta_i^l$ and θ_i^l, as well as the estimated total changes realized over the sample period.[8]

4 Data

The data used in this paper consist of two data sets covering 214 general hospitals operating in Switzerland from 1998 to 2003.[9] These data include a "hospital-level data set" based on hospitals' financial and administrative data (SFSO 1997a), and a "DRG-level data set" extracted from medical records of individual hospitalizations,[10] including the average LOS and the number of cases by hospital, year and DRG categories (SFSO 1997b). While the hospital-level data set is used for the analysis of cost-efficiency and excess capacity, the analysis of hospital stays is based on the DRG-level data. The latter data are also used to calculate an average DRG cost weight for each hospital-year that is merged into the hospital-level data. This average cost weight represents a measure of the severity of the patient mix, used for adjusting the number of admissions (more on this later).

The available data contain a number of missing values and invalid observations. In order to have a sufficient number of sample points over time, about 36 hospitals that have been covered for less than 3 years are excluded from the sample: In fact, the quadratic form of temporal changes requires at least three values for a reasonable identification of individual parameters. Moreover, an adequate efficiency analysis requires a sample of comparable hospitals that satisfy the basic assumptions of the model. Therefore, ten hospitals that have changed ownership status over the sample period are also excluded. Given that the ownership changes are probably related to efficiency reasons,

[7] I use the word *excess* in a narrow sense, to denote the temporal changes that cannot be explained by the changes in variables included in the model.

[8] Kruskal–Wallis test is a non-parametric test that has been often used in frontier analysis (Singh and Coelli 2001; Grosskopf et al. 2001). An alternative approach would be to include type indicators as interaction terms in the regression models and test their significance. I preferred the non-parametric test because of its robustness to distribution assumptions.

[9] Specialized clinics, rehabilitation centers and other long-term facilities are excluded.

[10] The original data base includes about a million records by DRG and admission categories.

assuming constant parameters for efficiency changes (δ_i, θ_i) is not realistic for these hospitals.[11] In addition a few extremely small hospitals (with less than ten beds) were excluded. Although officially classified as general hospitals, these hospitals appear to belong to a special category of local hospitals whose services might deviate from the short-term treatments commonly provided in general hospitals. The final hospital-level sample includes 863 observations from 168 general hospitals.[12]

As for the DRG-level data, the adopted sample has been restricted to the hospitals that have been included in the hospital-level data set and the observations that are based on three or more inpatient cases with hospitalizations longer than 24 h, from the DRG categories that have a clear definition[13] according to the Swiss AP-DRG classification version 4.0 (APDRG Suisse 2003). The final sample, after excluding severe outliers,[14] consists of 108,227 observations from 162 general hospitals, 492 AP-DRG categories, 826 hospital-year groups and 23,281 hospital-DRG groups. From the 492 DRG's included in the sample, 223 are classified as surgical procedures. In terms of the number of hospitals and the composition of hospital types regarding ownership, university hospitals and also the distribution across different regions, this sample is very similar to the hospital-level sample used for the analyses of cost and excess capacity. A descriptive summary of the main variables included in the models is provided in Table 1. In the rest of this section these variables will be described.

The main measure of hospital output is taken as a DRG adjusted number of hospitalizations (cf. Linna 1998; Rosko 2001; Heshmati 2002), obtained by multiplying total admissions by an average DRG cost weight calculated for each hospital-year.[15] Since the number of outpatient cases is not available in the data, the ambulatory output is approximated by the corresponding revenues adjusted for inflation. This approximation is based on the assumption that the average unit price of ambulatory care is similar across hospitals.

Three input factors are considered: capital, physicians' input and all other employees' labor. Similar to Wagstaff and Lopez (1995) and Rosko (2001), capital prices, are approximated by the hospital's total capital expenditure divided by the number of available beds in the hospital. Labor prices are calculated by dividing total salaries by the number of remunerated days. Physicians and non-physicians are considered as two separate labor inputs similar (cf. Folland and Hofler 2001; Scuffham et al. 1996). The physicians' labor price represents the average salary of those employed by the hospital and exclude honoraries and fees, accounting on average for about 5% of the hospital's total costs, usually paid to both employed and unemployed physicians. Both labor prices are proportionally adjusted for social benefits, accounting on average, for about 9% of total costs with the proportions being the respective shares of each group's salaries. This adjustment captures the potential variation in social benefits due to differences in pension funds as well as the age and seniority of the employees mix.

In line with most hospital cost studies in the literature (with a very few exceptions such as Rosko 2001), the input prices are assumed to be exogenous. This simplifying assumption usually reflects the difficulty of finding reasonable instrumental variables to account for such endogeneities. Here, the hospital fixed effects alleviate the problem, to the extent that the price endogeneity is time-invariant sources. Moreover, I argue that the problem is less severe in Switzerland, where given the strong restrictions in the labor market, the relative uniformity of capital markets, and the strong monitoring system for quality and maintenance, the hospitals' ability in affecting the prices are relatively limited.[16]

The three input factor prices considered in the model correspond to about 70% of total costs in a typical hospital included in the sample. The available data do not allow an appropriate calculation of the prices of remaining inputs such as medical materials, food, water and power as well as physicians' fees and other personnel charges. The excluded prices might vary over time and across hospitals. The time-

[11] Such an assumption might bias the estimated differences across different ownership types. Assuming a sudden structural change in parameters after the conversion year is also unrealistic, because the ownership changes are usually long processes and the converting hospitals might undergo gradual changes prior to conversion. See Farsi (2004) for some evidence on this issue.

[12] A series of probit analyses and *t*-tests indicated that the excluded observations are not related to an obvious selection of hospitals regarding size (number of beds) or ownership/subsidy types. In any case, given the presence of fixed effects in the model sample selection is not expected to affect the results.

[13] The DRGs described by 'other' or 'non-specified' were not considered.

[14] About 1,600 severe outliers with average LOS greater than 36.4 days (three times the inter-quartile range) were excluded.

[15] The average cost weight for any given hospital-year is calculated form the medical data, by dividing the weighted sum of the number of admissions (with weights being the DRG cost weights according to Swiss AP-DRG version 4.0), by the total number of cases. This provides a single measure of inpatient services in contrast with Brown's (2003) approach with multiple groups with similar DRG weights.

[16] In any case the focus of this study is on efficiency estimates and the endogeneity bias in the price coefficients is of secondary importance. The possible impact of endogeneity on efficiency estimates is an open question that depends on whether a company's intentions in changing their inputs are interpreted as a quality-neutral effort to improve efficiency or as an intentional change in the quality of inputs. In the latter case, by including the input prices we can provide more realistic values of efficiency adjusted for quality differences, even though the price coefficients are obviously biased.

Table 1 Descriptive statistics

	Mean	Std. Dev.	Min.	1st Quartile	Median	3rd Quartile	Max.
Hospital's total costs (CHF '000)	69,655	124,286	924	15,657	32,592	65,129	884,764
Number of hospitalizations	6,306	7,128	116	1,845	4,096	7,871	50,774
Number of hospitalizations (AP-DRG adjusted)	5,400	7,065	76	1,370	3,123	6,568	49,251
Average total cost per hospitalization (CHF '000)	10.02	6.38	1.76	7.04	8.74	11.21	90.13
Number of patient-days	51,619	58,348	1,068	19,570	32,470	57,419	410,140
Average length of hospitalizations (days)[a]	10.4	6.6	2.0	6.6	8.4	11.5	57.6
Hospiatl's outpatient revenues (CHF '000)	10,752	20,458	0	1,301	4,118	10,281	144,802
Hospital capacity (number of beds)	175.2	202.0	12	63	104	210	1277
Excess capacity (average # of empty beds)	35.1	52.3	1	10	20	40	523
P_K (capital price) CHF '000 per bed	28.04	26.68	1.46	11.05	17.19	36.28	242.57
P_L-physicians[b] (CHF per day)	334.51	114.22	66.80	263.03	321.15	393.43	781.63
P_L-other employees[c] (CHF per day)	178.11	33.09	69.43	158.91	176.98	196.85	302.01
Number of medical training position	41.6	91.3	1	6	14	31	583
Share of private-insurance admissions[d]	0.28	0.22	0.00	0.15	0.22	0.31	1
Average length of full hospitalizations excluding semi-hospitalizations (days)							
Hospital-level sample	11.3	6.4	3.7	7.8	9.0	12.3	57.6
DRG-level sample	9.7	6.1	1.0	5.2	8.0	12.6	36.3
Average AP-DRG cost weight							
Hospital-level sample	0.806	0.110	0.520	0.740	0.789	0.854	1.334
DRG-level sample	1.008	0.783	0.112	0.582	0.795	1.161	21.597

Unless stated otherwise, the numbers are based on the hospital-level sample

The hospital-level sample includes 863 observations from 168 hospitals (1998–2003)

The DRG-level sample includes 108,227 observations from 492 AP-DRG categories

All monetary values are adjusted by the global consumer price index relative to 2003 prices

[a] Semi-hospitalizations (shorter than 24 h) are considered as 1-day hospitalizations

[b] Employed physicians' average salary, adjusted for social benefits and excludes fees

[c] Average salary (adjusted for social benefits) of all hospital employees except physicians

[d] Based on hospital discharges; includes cases with private and semi-private insurance

invariant differences are captured by the hospital fixed effects, thus cannot bias the results. As for the temporal variations in the excluded prices, they are partly captured by the time variables included in the cost model, otherwise are assumed to be uncorrelated with temporal variations of efficiency.

The average length of hospitalization has been included in the model (Vita 1990; Scuffham et al. 1996; Carey 1997). In addition to representing hospital's 'hotel services' like nursing care and accommodation (Breyer 1987), this variable provides a measure of severity of the case mix within each DRG. In fact, there is a considerable variation among patients within a DRG, as indicated by the wide range of acceptable hospitalization length provided by the Swiss DRG Association (APDRG Suisse 2003).

Hospitals' costs can also be affected by the number of specializations and services offered in a hospital. Here we assume that these factors are time-invariant, thus captured by the fixed effects. The shortcoming of the analysis is mainly related to the quality of care. In fact, it is reasonable to consider that by improving cost-efficiency, certain quality aspects of health care might be compromised. We do not have any reliable data on any measure of quality in Swiss hospitals that show a reasonable variation over the sample period. It should be however noted that the evidence on the effect of quality measures on hospital costs is not conclusive. Zuckermann et al. (1994), Rosko (2001) and Vitaliano and Toren (1996) conclude that quality indicators do not have significant cost effects, whereas others such as Folland and Hofler (2001) suggest a significant effect for structural quality measures such as bed availability and the share of board-certified physicians.

The measure of excess capacity is based on the average number of empty beds in a given hospital-year. This is obtained by subtracting the number of available beds by the total number of patient days divided by 365. The semi-hospitalizations (inpatient stays shorter than 24 h) are considered as 1-day hospitalization. The data show some discrepancy in this measure particularly several negative values. These values have been re-calculated using an

Table 2 Number of hospitals by category (1998–2003)

Ownership/subsidy status	Frequency	Percent
Non-subsidized for-profit (FP)	27	16.07
Non-subsidized non-profit (NP)	16	9.52
Public (PUB)	81	48.21
Private subsidized (SUB)	44	26.19
Total	168	100

alternative measure of hospital's available beds namely, the number of hospital's bed-days. The ownership status and subsidization form have been considered in four categories as described in Table 2.

5 Results

Table 3 provides the regression results of the hospital-level analysis based on Eqs. 4, 6 and 8, respectively for total costs, excess capacity and LOS. The results of the cost model point to considerable effects of hospital stays on costs. The variation of other factors such as ambulatory services and the training positions though being statistically significant are practically limited to a few percentage points in terms of elasticity. The estimated coefficients are mostly significant and generally have the expected signs. As discussed earlier, considering that the between-hospital variations are entirely suppressed in the hospitals' individual fixed effects, the estimated coefficients here might be inadequate for any inference about the technological characteristics such as returns to scale.[17] Therefore, in the following discussion we focus on the efficiency estimates and their variations.

The estimation results of the cost analysis (Table 3) point to a pattern of increasing growth in hospital' operating costs, as suggested by the positive coefficients of the time variables with an average growth rate of about 1.6% per year. The results also suggest that the temporal changes are significantly different from one hospital to another, as shown by the statistically significant values for the variance of the random effects. The negative covariance between the two random coefficients is consistent with the fact that any growth (decline) is likely to slow down with time. The negative correlation implies for instance, that hospitals that start to cut the costs earlier and more aggressively, will have a relatively lower success later.

The estimation results from the analysis of excess capacity (Table 3, the middle column) indicate that hospitals have decreased their empty beds with a substantial average rate of about 8.6% per year. The negative effect of number of admissions suggests that hospitals with greater outputs have been downsizing more, perhaps because of their greater margins for demand fluctuations.[18] As expected the share of private-insurance patients shows a positive effect on excess capacity, however, the coefficient is not statistically significant. Similarly the results indicate significant variation across hospitals regarding the empty beds.

Finally the last column (Table 3) provides the results of the DRG-level analysis of the length of hospitalizations. As seen in the table, the estimated annual rate of decrease in LOS is about 2% on average. The number of training positions has a positive but statistically insignificant on LOS. The fixed effects at the hospital-DRG groups are expected to capture the differences among DRGs regarding the potentials for reducing LOS, thus decreasing the possible aggregation biases due to different distributions of DRGs across hospitals.[19] These results also indicate a significant variation LOS's temporal variations, across the included hospitals and also among the DRG groups.

The considerable variation of temporal patterns across individual hospitals suggests that the study of the variations between hospital types could be used to test hypotheses regarding the efficiency patterns in the hospital sector. Before turning to the results of these statistical tests, it is worthwhile to summarize the overall efficiency trends. The average estimated time effects from Table 3 are illustrated in Figure 1. These variations are obtained from Eq. 11 averaged over hospitals. As can be seen in the figure, over the 5-year span in the sample period (1998–2003) a typical hospital's costs have grown about 14%. This is while the length of hospital stays and the number of empty beds have decreased by about 10% and 18% respectively. The substantial rate of decline in LOS and hospital empty beds shown in the figure is indicative of hospitals' considerable efforts to contain costs.

The considerable growth in the sector's costs is consistent with the growth of hospital costs in many countries, reported in previous literature. This growth has been often associated with new medical procedures and pharmaceuticals as well as the extension of life expectancy. These are obviously *external* factors that are modeled by average

[17] The presence of fixed effects can also explain the lack of statistical significance for some of the variables. Compare for instance with the estimation results reported in Farsi and Filippini (2008).

[18] This can also be explained by the mechanical negative relationship between admissions and the number of empty beds. Such a relationship might create endogeneity bias in the hospital-specific estimates of growth in excess capacity. However, a preliminary analysis showed that excluding the number of admissions from the model does not cause much difference.

[19] An additional analysis of LOS aggregated at the hospital level (available upon request), indicates an average decrease of about 3.3% per year in the length of hospitalizations, suggesting an upward aggregation bias. All other coefficients are very similar to those reported in Table 3.

Table 3 Estimation results

	Total costs	Excess capacity	Length-of-stay
Number of hospitalizations (AP-DRG adjusted)	0.300*		
	(0.018)		
Outpatient revenues	0.025*		
	(0.008)		
Average length of hospitalizations	0.228*		
	(0.022)		
P_K (capital price)	0.124*		
	(0.008)		
P_L-physicians	0.008 (0.013)		
P_L-others	0.050*		
	(0.021)		
Number of training positions	0.021*		0.0046
	(0.010)		(0.0046)
Time (linear trend)	0.016*	−0.086*	−0.019*
	(0.006)	(0.035)	(0.0022)
Time (squared)	0.002*	0.010	−0.00034
	(0.001)	(0.006)	(0.00039)
Number of hospitalizations		−0.447*	
		(0.112)	
Share of private-insurance admissions		0.147	
		(0.208)	
σ_1	0.062*	0.317*	0.187*
	(0.006)	(0.036)	(0.0027)
σ_2	0.011*	0.053*	0.032*
	(0.001)	(0.007)	(0.00051)
σ_{12}	−0.894*	−0.915*	−0.936*
	(0.027)	(.024)	(0.0023)
σ_ε	0.040*	0.287*	0.220*
	(0.001)	(0.009)	(0.00061)
Log likelihood (restricted)	1288.16	−305.90	−1958.14
Number of observations	863	863	108,227
Observation unit	Hospital-year	Hospital-year	DRG-hospital-year

* Means significant at 5%; Standard errors are given in parentheses; all variables except share of private insurance admissions are in logarithms; the hospital-level sample includes 863 records from 168 hospitals; the DRG-level sample includes 108,227 observations from 492 AP-DRG's treated in 162 hospitals; the sample period covers from 1998 through 2003

trends in the model specification used in this paper. The hospital-specific inefficiency is defined as the hospital's excess costs as compared to the average increasing trend shown in Fig. 1. A useful way of investigation the relationships between costs and other measures, is by dividing the sample into two groups namely hospitals that improved on cost-efficiency and those who showed an efficiency loss. These two groups correspond respectively to negative and positive values for Δu_i at the end of the sample period ($t = 5$) obtained from Eq. 11. The average temporal variations of excess costs, capacity and LOS in these two groups are depicted in Figs. 2 and 3, respectively.

Figure 2 shows that the 81 hospitals that had an efficiency gain (in costs) have also considerably cut their hospital stays and empty beds. Compared to the overall patterns in Fig. 1, these hospitals, while having a relatively high reduction in excess capacity, are not much different from average in terms of LOS. Similarly, the average changes in excess LOS the 87 hospitals with declining cost efficiency over the sample period (Fig. 3) show a change of LOS that is totally comparable to the overall average trends (Fig. 1). However, the excess capacity takes a somewhat milder reduction here. The trends in both groups of hospitals show an average change of about 8% points in cost-efficiency over the sample period. This might suggest a reasonable targeting benchmark that is comparable to the 2–3% annual efficiency gain targets set by the UK health care authorities (Jacobs and Dawson 2003).

A comparison between Figs. 2 and 3 points to a distinctive difference in excess capacity changes between the two groups, suggesting that empty beds have a crucial impact on cost-efficiency. However, it should be noted that

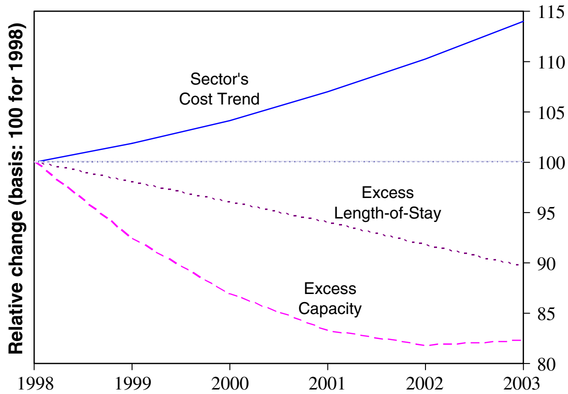

Fig. 1 Temporal variation of costs, excess capacity and LOS (168 hospitals)

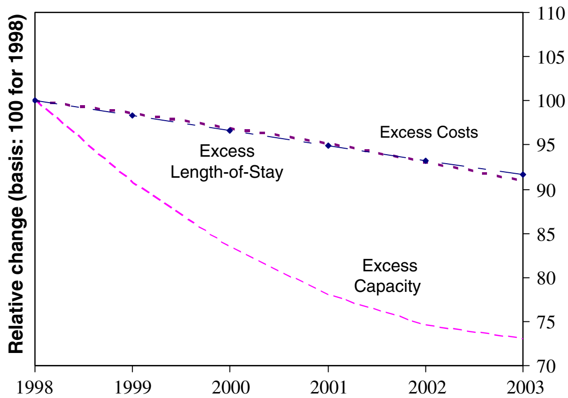

Fig. 2 Variations in hospitals that improved in cost-efficiency (81 hospitals)

the variation among individual hospitals are ignored in the average trends illustrated in these figures.[20] A statistical analysis of the correlations between these efficiency measures can be used to assess the relative importance of hospital stays and excess capacity.

The differences between ownership/subsidy groups listed in Table 2 are analyzed with a series of Kruskal–Wallis and t-tests with unequal variances. The results generally suggest that the differences across hospital types are due to sampling error, not a systematic difference in the underlying distribution. The observed significance level was

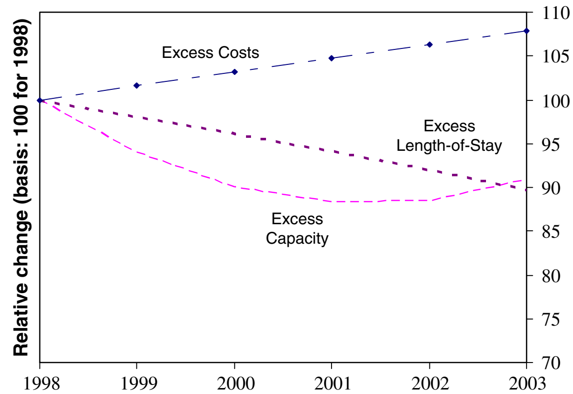

Fig. 3 Variations in hospitals that declined in cost-efficiency (87 hospitals)

generally higher than 10% and the results were confirmed using only the linear trends or the resulting change over the 5-year span of the sample. Similar results were obtained for all three measures namely, changes in cost-efficiency, excess capacity and LOS.

Noting that the variation among individual hospitals often dominates the variations between hospital types,[21] an important question is whether improvement in cost-efficiency are positively correlated with other measures like limiting the empty beds and shortening hospitalizations, presumably aimed at cost reductions. In order to see an overall picture, the correlation matrix between these measures is provided in Table 4. The listed coefficients are based on Spearman's rank correlation between the estimated rises for each hospital over the 5-year span, obtained by substituting $t = 5$ in Eq. 11. The correlation coefficients are also provided for the two sub-samples with a gain or loss in cost-efficiency, corresponding to $\Delta u_i(t = 5)$ smaller or greater than zero respectively.

The numbers estimated on the entire sample (first two columns) indicate a positive and significant correlation between efficiency measures related to excess cost and excess capacity suggesting that hospitals that have been able to decrease the empty beds are also successful in cutting costs. This statement does not apply to hospital stays: The null hypothesis of independence between excess costs and excess LOS cannot be rejected at any reasonable

[20] Interpreting the average trends without statistical correlations, could be misleading. For instance, as we see later the excess costs and excess LOS show a positive correlation in the hospital group with efficiency loss, which might seem contradictory to the opposing trends in costs and LOS in Fig. 3. However, a positive correlation does not necessarily imply similar average trends. Rather, it implies that the hospitals that are located above the LOS curve are likely to be above the excess capacity curve as well. Another interesting point is the close coincidence of LOS and cost curves in Fig. 2, but the lack of statistically significant correlation between the two measures in that group (as we see later).

[21] In addition to ownership types, we studied the differences among five *typologies* based on size and specialization (SFSO 2001), and five geographical regions (details available upon request). Virtually in all cases, the differences across groups were statistically insignificant. The only exception was canton Ticino (southern region) with greater gains in cost efficiency compared to four other regions. Nevertheless, further tests suggested no significant difference between Ticino and six other cantons (BS, BL, FR, GE, NE and VS), out of 26 Swiss cantons.

Table 4 Spearman's rank correlation between three measures of growth between 1998 and 2003

	Overall ($N = 168$ hospitals)		Hospitals showing an improvement in cost-efficiency ($N = 81$)		Hospitals showing a decline in cost-efficiency ($N = 87$)	
	Excess capacity	Excess length-of-stay	Excess capacity	Excess LOS	Excess capacity	Excess LOS
Excess costs	0.200**	−0.054	0.244**	−0.038	0.021	0.202*
Ex. capacity	1	−0.184**	1	−0.175	1	−0.176
Average decrease (%):	17.7	9.7	27.0	9.1	9.1	10.3

* Significant at 10%; ** Significant at 5%

significance level.[22] However, the correlation patterns within the two sub-samples (Table 4) point to certain differences between hospitals showing efficiency gains and losses: In particular, there is a borderline significant and positive correlation between excess costs and excess LOS in hospitals that have shown a decline in cost-efficiency. This finding suggests that among hospitals with relatively poor performance regarding efficiency gains, thus perhaps with certain slackness in excess LOS, curtailing hospital stays could be an effective means for improving cost efficiency. On the other hand, in these hospitals there is no significant correlation between excess capacity and excess costs, suggesting that lowering excess capacity does not necessarily bring about any cost savings. This can be explained by the fact that in these hospitals the apparently low excess capacity might be a result of excessively long hospitalizations.

Finally, the numbers in Table 4 suggest a negative correlation between temporal changes in excess capacity and excess LOS. However, this correlation is not statistically significant within each one of the two sub-samples. Considering that in the short-run, empty beds increase as a result of reduction of hospital stays, this finding suggests that at least in some hospitals, shortening LOS is not completed by sufficient follow-up measures to reduce the resulting excess capacity.

6 Conclusions

Using a panel data mixed effects model we proposed an econometric specification inspired by Sickles' (2005) general models, for the analysis of temporal variations in Swiss hospitals' productive efficiency. The model includes fixed effects for unobserved time-invariant factors related to individual hospitals and DRG categories, and random coefficients representing the effects of time variables. The measures of interest are the hospitals' gains in cost-efficiency, the realized cuts in empty beds and the shortening of hospitalizations over the period starting from 1998 which coincides approximately with the outset of health policy reforms particularly the gradual implementation of prospective payment system in Switzerland.

The results indicate that on average the length of hospitalization and the number of empty beds in a hospital have decreased by about 10% and 18%, respectively. The results also suggest that after adjusting for the changes in outputs, labor prices and other characteristics such as teaching activities, hospital costs have risen considerably and increasingly over the 6-year period from 1998 to 2003, amounting to an average increase of 14% in total costs for a typical hospital. It is assumed that this overall increase reflects the external factors such as progress in medical treatments and extension of life expectancy, and the remaining hospital-specific changes in costs are associated with efficiency gains or losses.

There is a considerable variation among individual hospitals concerning cost efficiency gains and also the efforts in cutting the excess capacity and curtailing hospitalizations. In general hospitals that showed a relatively important decrease in excess capacity are likely to show a relative gain in cost-efficiency and *vice versa*. However, the results do not provide any conclusive evidence that gains in cost efficiency be associated with shortening hospital stays. Interestingly, only among hospitals that experienced an efficiency loss over the sample period, relatively low cuts in hospitalization length are likely to be associated with the hospitals with low efficiency gains, suggesting that the length of stay could be an important parameter in these hospitals. This result can also be interpreted as suggestive evidence that hospitals that have a good performance in containing costs do not have much slackness in their hospitalization lengths. While confirming the strong heterogeneity across hospitals regarding efficiency gains, the findings do not provide any evidence in favor of a particular ownership/subsidization type.

The adopted methodology is readily applicable to other industries and the assumptions are easy to understand and interpret. In addition, in line with several models in this field (probably starting from Cornwell et al. 1990) the

[22] This result was also confirmed by a series of correlation analyses within various types of hospitals by ownership/subsidy. Excepting a few cases with significant correlations in levels, the rank correlation remained statistically insignificant across all sub-samples.

efficiency estimates do not rely on the skewness of the residuals. The combination of fixed effects with random effects, allows a complete abstraction from the unobserved time-invariant variables whose effects are not primordial for the analysis (fixed effects) while at the same time providing a 'statistically' efficient estimation basis for the parameters of interest (random effects).

Given that in presence of strong unobserved heterogeneity, the time-invariant component of efficiency is difficult if at all possible to identify, reliable measures of efficiency gains over time can be helpful in many regulation and policy applications. This paper illustrates that with certain assumptions, panel data mixed effects can be used for this purpose. However, it is important to consider the implications of the model's assumptions in each specific application and the resulting policy limitations. In the case studied here, the results are based on the assumption that the potential changes in the unobserved quality of hospital services in response to the reforms and financial pressures, are either uniform across the sector or uncorrelated with the adopted measures of efficiency improvement. Therefore, any possibility of deviation form this assumption should be considered before drawing relevant policy conclusions.

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References

Aigner D, Lovell CAK, Schmidt P (1977) Formulation and estimation of stochastic frontier production function models. J Econom 6:21–37. doi:10.1016/0304-4076(77)90052-5

Alvarez AM, Schmidt P (2006) Is skill more important than luck in explaining fish catches? J Prod Anal 26(1):15–25. doi:10.1007/s11123-006-0002-x

APDRG Suisse (2003) Cost Weights version 4.1. Institut de Santé et d'Economie Prilly, Switzerland, available at: www.apdrgsuisse.ch

Battese GE, Coelli T (1992) Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. J Prod Anal 3:153–169. doi:10.1007/BF00158774

Bradford WD et al (2001) Stochastic frontier estimation of cost models within the hospital. Rev Econ Stat 83(2):302–309. doi:10.1162/00346530151143833

Breyer F (1987) The specification of a hospital cost function: a comment on the recent literature. J Health Econ 6:147–157. doi:10.1016/0167-6296(87)90004-X

Brown HS (2003) Managed care and technical efficiency. Health Econ 12(2):149–158. doi:10.1002/hec.712

Carey K (1997) A panel data design for estimation of hospital cost functions. Rev Econ Stat 79(2):443–453. doi:10.1162/003465300556850

Carey K (2000) Hospital cost containment and length of stay: an econometric analysis. Southern Econ J 67(2):363–380. doi:10.2307/1061475

Cornwell Ch, Schmidt P, Sickles RC (1990) Production frontiers with cross-sectional and time-series variation in efficiency levels. J Econom 46:185–200. doi:10.1016/0304-4076(90)90054-W

Deily ME, McKay NL (2006) Cost inefficiency and mortality rates in Florida hospitals. Health Econ 15(4):419–431. doi:10.1002/hec.1078

Farsi M (2004) Changes in hospital quality after conversion in ownership status. Int J Health Care Finance Econ 4(3):211–230. doi:10.1023/B:IHFE.0000036047.66483.46

Farsi M, Filippini M (2004) Regulation and measuring cost efficiency with panel data models application to electricity distribution utilities. Rev Ind Organ 25(1):1–19. doi:10.1023/B:REIO.0000040474.83556.54

Farsi M, Filippini M (2006) An analysis of efficiency and productivity in Swiss hospitals. Schweiz Z Volkswirtsch Stat 142(1):1–37

Farsi M, Filippini M (2008) Effects of Subsidization and Teaching Activities on Hospital Costs in Switzerland. Health Econ 17(3): 335–350

Farsi M, Filippini M, Kuenzle M (2005) Unobserved heterogeneity in stochastic cost frontier models: an application to Swiss nursing homes. Appl Econ 37:2127–2141. doi:10.1080/00036840500293201

Folland ST, Hofler RA (2001) How reliable are hospital efficiency estimates? Exploiting the dual to homothetic production. Health Econ 10:683–698. doi:10.1002/hec.600

Gaynor M, Anderson GF (1995) Uncertain demand, the structure of hospital costs, and the cost of empty hospital beds. J Health Econ 14:291–317. doi:10.1016/0167-6296(95)00004-2

Greene W (2005) Fixed and random effects in stochastic frontier models. J Prod Anal 23(1):7–32. doi:10.1007/s11123-004-8545-1

Grosskopf S, Margaritis D, Valdmanis V (2001) Comparing teaching and non-teaching hospitals: a frontier approach (teaching vs. non-teaching hospitals). Health Care Manage Sci 4:83–90. doi:10.1023/A:1011449425940

Heshmati A (2002) Productivity measurement in Swedish departments of gynecology and obstetrics. Struct Change Dynam 13:315–336. doi:10.1016/S0954-349X(01)00040-6

Hollingsworth B, Street A (2006) The market for efficiency analysis of health care organisations (editorial). Health Econ 15(11):1055–1059. doi:10.1002/hec.1169

Jacobs R, Dawson D (2003) Hospital efficiency targets. Health Econ 12(8):669–684. doi:10.1002/hec.758

Jacobs R, Smith PC, Street A (2006) Measuring efficiency in health care: analytic techniques and health policy. Cambridge University Press

Kneip A, Sickles RC, Song WH (2003) On estimating a mixed effects model with applications to the US banking industry. Rice University, Mimeo

Kruskal WH, Wallis WA (1952) Use of ranks in one-criterion variance analysis. J Am Stat Assoc 47:583–621. doi:10.2307/2280779

Kumbhakar SC (1990) Production frontiers and panel data, and time varying technical inefficiency. J Econom 46:201–211. doi:10.1016/0304-4076(90)90055-X

Kumbhakar SC (1991) Estimation of technical inefficiency in panel data models with firm- and time-specific effects. Econ Lett 36:43–48. doi:10.1016/0165-1765(91)90053-N

Lee Y, Schmidt P (1993) A production frontier model; with flexible temporal variation in technical efficiency. In: Fried H, Lovell K, Schmidt S (eds) The measurement of productive efficiency. Oxford University Press, New York

Linna M (1998) Measuring hospital cost efficiency with panel data models. Health Econ 7:415–427. doi :10.1002/(SICI)1099-1050(199808)7:5<415::AID-HEC357>3.0.CO;2-9

Liu C, Laporte A, Ferguson B (2007) The Quantile Regression Approach to Efficiency Measurement: Insights from Monte Carlo Simulations, HEDG Working Paper 07/14, Department of Economics, University of York

Martin S, Smith P (1996) Explaining variations in inpatient length of stay in the National Health Service. J Health Econ 15:279–304. doi:10.1016/0167-6296(96)00003-3

Meeusen W, van den Broeck J (1977) Efficiency estimation from Cobb–Douglas production functions with composed error. Int Econ Rev 18(2):435–444. doi:10.2307/2525757

Mundlak Y (1978) On the pooling of time series and cross section data. Econometrica 64(1):69–85. doi:10.2307/1913646

Newhouse JP (1994) Frontier estimation: how useful a tool for health economics. J Health Econ 13:317–322. doi:10.1016/0167-6296(94)90030-2

Polachek S, Yoon B (1996) Panel estimates of a two-tiered earnings frontier. J Appl Econom 11:169–178. doi :10.1002/(SICI)1099-1255(199603)11:2<169::AID-JAE373>3.0.CO;2-#

Rosko MD (2001) Cost efficiency of US hospitals: a stochastic frontier approach. Health Econ 10:539–551. doi:10.1002/hec.607

Rogowski JA, Newhouse JP (1992) Estimating the indirect costs of teaching. J Health Econ 11:153–171. doi:10.1016/0167-6296(92)90032-V

Schmidt P, Sickles RC (1984) Production frontiers and panel data. J Bus Econ Stat 2:367–374. doi:10.2307/1391278

Scuffham PA, Devlin NJ, Jaforullah M (1996) The structure of costs and production in New Zealand public hospitals: an application of the transcendental logarithmic variable cost function. Appl Econ 28:75–85. doi:10.1080/00036849600000010

SFSO (1997a) Statistiques des établissements de santé (soins intra-muros), Statistique des hôpitaux, Conception détaillée, Déc. 1997 (in French). Swiss Federal Statistical Office, Neuchâtel, Switzerland, www.statistik.admin.ch

SFSO (1997b) Statistiques des établissements de santé (soins intra-muros), Statistique médicale des hôpitaux, Conception détaillée 1997 (in French). Swiss Federal Statistical Office, Neuchâtel, Switzerland, www.statistik.admin.ch

SFSO (2001) Statistiques des établissements de santé (soins intra-muros), Typologie des hôpitaux (in French). Swiss Federal Statistical Office, Neuchâtel, Switzerland, www.statistik.admin.ch

Sickles RC (2005) Panel estimators and the identification of firm-specific efficiency levels in parametric, semiparametric and nonparametric settings. J Econom 126(2):305–334. doi:10.1016/j.jeconom.2004.05.004

Simmer T, Nerenz D, Rutt W, Newcomb C, Benfer C (1991) A randomized, controlled trial of an attending staff service in general internal medicine. Medical Care 29(7):31–40

Singh S, Coelli T (2001) Performance of dairy plants in the cooperative and private sectors in India. Ann Public Coop Econ 72(4):453–479. doi:10.1111/1467-8292.00178

Skinner J (1994) What do stochastic frontier cost functions tell us about inefficiency? J Health Econ 13:323–328. doi:10.1016/0167-6296(94)90031-0

Steinmann L, Zweifel P (2003) On the (in)efficiency of Swiss hospitals. Appl Econ 35:361–370. doi:10.1080/00036840210167183

Street A (2003) How much confidence should we place in efficiency estimates? Health Econ 12:895–907. doi:10.1002/hec.773

Vita MG (1990) Exploring hospital production relationships with flexible functional forms. J Health Econ 9:1–21. doi:10.1016/0167-6296(90)90038-5

Vitaliano D, Toren M (1996) Hospital cost and efficiency in a regime of stringent regulation. East Econ J 22:161–184

Wagstaff A, Lopez G (1995) Hospital costs in Catalonia: a stochastic frontier analysis. Appl Econ Lett 3:471–474. doi:10.1080/758540809

Worthington AC (2004) Frontier efficiency measurement in health care: a review of empirical techniques and selected applications. Med Care Res Rev 61(2):135–170. doi:10.1177/1077558704263796

Zuckerman S, Hadley J, Iezzoni L (1994) Measuring hospital efficiency with frontier cost functions. J Health Econ 13:255–280. doi:10.1016/0167-6296(94)90027-2