



**University of
Zurich** ^{UZH}

University of Zurich
Department of Economics

Working Paper Series

ISSN 1664-7041 (print)
ISSN 1664-705X (online)

Working Paper No. 53

**Does Prospective Payment Increase Hospital
(In)Efficiency? Evidence from the Swiss Hospital
Sector**

Philippe K. Widmer

December 2011

Does Prospective Payment Increase Hospital (In)Efficiency? Evidence from the Swiss Hospital Sector

Philippe K. Widmer^{a,*}

^a*Department of Economics, University of Zurich*

Abstract

Several European countries have followed the United States in introducing prospective payment for hospitals with the expectation of achieving cost efficiency gains. This article examines whether theoretical expectations of cost efficiency gains can be empirically confirmed. In contrast to previous studies, the analysis of Switzerland provides a comparison of a retrospective per diem payment system with a prospective global budget and a payment per patient case system. Using a sample of approximately 90 public financed Swiss hospitals during the years 2004 to 2009 and Bayesian inference of a standard and a random parameter frontier model, cost efficiency gains are found, particularly with a payment per patient case system. Payment systems designed to put hospitals at operating risk are more effective than retrospective payment systems. However, hospitals are heterogeneous with respect to their production technologies, making a random parameter frontier model the superior specification for Switzerland.¹

Keywords: hospital inefficiency, prospective payment system, Bayesian inference, stochastic frontier analysis

JEL: C11, C23, D24, I18

¹ Author's Note: The author would like to thank Alexander Ziegenbein for his efforts in the data collection.

* Corresponding author: Philippe Widmer, Department of Economics, University of Zurich, Hottingerstrasse 10, CH-8032 Zurich, Switzerland. Phone: +41 (0)44 634 22 70, Fax: +41 44 634 49 87, E-mail: philippe.widmer@econ.uzh.ch

1. Introduction

Growing health care expenditures over the last several decades have highlighted the need for health care reforms in order to contain future cost increases. One promising approach, which was first implemented in the U.S. and was recently adapted by many European countries, involves the transition from retrospective (RPS) to prospective (PPS) hospital payment systems (see Smith, 2004 and Schneider, 2007 for an overview of Europe's reforms). The assumption is that a change to predetermined and fixed payments would place hospitals at operating risk and would increase their cost efficiency.

Even though there are convincing theoretical arguments for cost reductions and efficiency gains (Biorn et al., 2003; Chalkley and Malcomson, 1998; Newhouse, 1996), empirical literature is lacking. The linkage between efficiency gains and PPS has yet to be demonstrated for the U.S. Medicare reform of 1983, which switched from RPS to a payment per patient case system, or for any of the European countries that moved from RPS to a payment per patient case or a global budget system (see Section 2 for further information on the payment systems). For example, Borden (1988) found no significant efficiency gains for 93 New Jersey hospitals from the years 1979 to 1984. Similar results were obtained by Chern and Wan (2000) when they examined the catch-up effect of technically inefficient hospitals in Virginia from 1984 to 1993. Inefficient hospitals became even more inefficient in 1993, which is contrary to the expectations of PPS. However, efficiency gains were shown by Morey and Dittman (1996), who analyzed the technical inefficiency of 105 hospitals in North Carolina. The results of European reforms remain inconclusive. While no efficiency gains were found in Austrian hospitals after funding shifted from per diem payments to global budgets in 1997 (Sommersguter-Reichmann, 2000), gains were found in Portugal (Dismuke and Sena, 1999), Finland (Linna, 1999), and Norway (Biorn et al. (2006)). Thus, hospital costs could even increase with PPS. Since PPS is well known to be concurrent to higher administration and supervising costs, which is not yet included in theoretical models, the incentive for cost reduction could be overstated.

However, these inconclusive results are most likely due to a lack of analytical rigor. In particular, although it is widely accepted that hospitals are rather heterogeneous in their production of health care services (Widmer et al., 2010), previously applied Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) have been restricted to homogeneous technology. Furthermore, it is well known that results of the frequently applied two-stage DEA approach are biased since it does not account for a possible correlation of the independent variables with the inputs and outputs of the first-stage DEA (Simar and Wilson, 2000). Finally, since most countries only recently switched to PPS at the country level, the time series available for within treatment analysis have been very

short. Most studies analyze a time period of four to five years, which may be too short for any reliable conclusion to be drawn. For instance, any changes could be driven by unobserved exogenous shocks, such as new medical technologies or inflation, that occurred concurrent with the implementation of PPS (Linna, 1999).

In order to overcome the limitations of previous studies, this article compares a retrospective per diem system with a prospective global budget and a payment per patient case system using data from Switzerland, where some member states changed to different variants of PPS while others remained with RPS. The contribution of this article is twofold. First, it extends previous work by implementing a random parameter frontier model to control for the importance of unobserved heterogeneity among six hospital categories and addresses whether empirical results significantly depend on the assumptions made for the production technology. Second, it determines whether theoretical expectations for cost savings can be confirmed in empirical analysis by relating calculated inefficiency scores to the three payment systems. Estimates are derived by an extended single-step approach of Battese and Coelli (1995).

The empirical analysis reveals two key results. First, with respect to model comparison, the random parameter frontier model is more robust and has a higher explanatory power than the single cost frontier model. Heterogeneity correction among hospital categories is crucial in deriving meaningful inefficiency scores. Second, PPS are negatively correlated with hospital cost inefficiency, particularly the payment per patient case system. Payment systems designed to put hospitals at operating risk are more effective than retrospective payment systems in containing health care costs.

The remainder of this paper is structured as follows. Section 2 gives an overview of the different prospective and retrospective payment systems that coexisted in Switzerland between 2004 and 2009. Section 3 outlines the standard and random parameter frontier model and Section 4 describes the data used as well as the empirical specifications. Finally, Section 5 presents the results of the cost frontier models and the determinants of inefficiency.

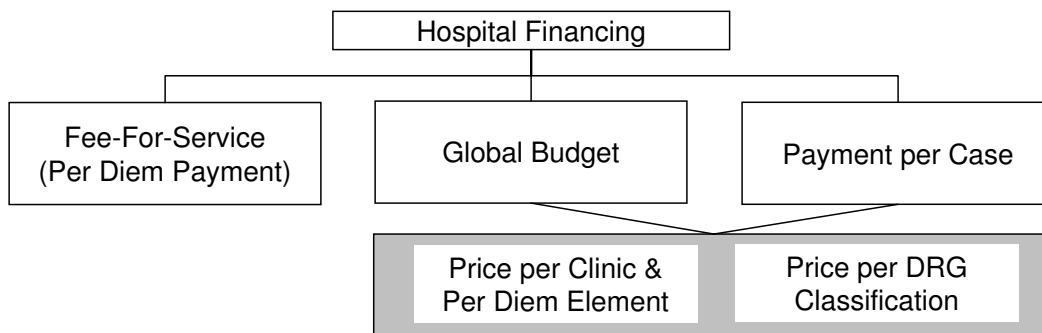
2. Introduction to Swiss Hospital Financing

The Swiss health care system has been shaped by the country's decentralized federal structure, in which all 26 member states (cantons) are responsible for providing health care services to their residents. The hospital sector is no exception. Cantonal authorities are responsible for capacity planning and for the quality of hospital care. Provision is typically purchased from hospitals that are qualified to provide health care to primary insured patients. However, this does not imply that hospital financing only comes from cantonal sources. On the contrary, health insurers pay an agreed

amount of up to 45 percent of operating costs, resulting in a dual system where cantons cover the residual cost and investments in infrastructure.² Modes of financing can therefore differ among cantons.

Increasing health care costs have induced many cantons to revise their hospital payment system. Especially the implementation of the new federal law on social health care insurance in 1994 (effective in 1996), where cantonal authorities were given legislative power to control for hospital operating costs, has resulted in the coexistence of various RPS and PPS in Switzerland (see Figure 1 for an overview of existing payment systems).

Figure 1: Swiss Payment Systems



Prior to 1996, cantons primarily used a retrospective cost-based per diem or fee-for-service system to pay hospitals for their services. Remuneration was equal to reported costs and bankruptcy was only possible if cantonal authorities decided to reduce overcapacity. Unsurprisingly, critics of these schemes argued that there was little incentive for cost containment. Hospitals could waste resources and increase health care costs in order to obtain greater reimbursement. Hence, after 1996, several cantons experimented with PPS to set incentives for cost containment. The two alternatives included a global budget and a payment per patient case system (see second level in Figure 1). Under a global budget system, hospitals are paid a fixed amount for a predetermined number of admissions whether or not a patient seeks care during the accounting period. Under a payment per patient case system, hospitals are paid a fixed amount per admission, regardless of the actual cost. In both cases, hospitals obtain the gain or incur the loss, making them act to minimize costs. However, the incentive for cost minimization could be weakened in the Swiss case because many cantons still do not firmly exclude a bailout. This is especially the case in a global budget system, where hospitals are

² Health care insurers might cover more than 45 percent of expenditures in privately owned hospitals, which are not on the cantonal list. However, these are typically for-profit hospitals specializing in supplementary insured patients.

generally allowed to renegotiate their budget for unexpected costs. Hospitals still have an implicit deficit guaranty which reduces their operating risk and therefore the incentive for cost minimization. Furthermore, the determination of the remuneration per admission could also influence incentives for cost containment. Two variants are widely used in Switzerland (see third level in Figure 1). The first variant determines payments per admission according to a clinic-specific average price and a per diem element to control for differences in the length of stay. The second variant uses a Swiss specification of the DRG classification system that attempts to classify patients into groups with similar usage of resource. In contrast to the first variant, payments are independent of the length of stay. Thus, hospitals have no incentives to maximize the length of stay, which should result in additional cost savings. Even in a DRG system there is provision for additional payment for those patients who are unusually expensive within the DRG classification, but these outlier payments apply to only a small portion of patients and are not directly related to length of stay.

An increasing number of cantons have changed to PPS. In 2004, only 38 percent of all Swiss hospitals were still reimbursed by per diem payments. Most hospitals had PPS and almost 36 percent of them already used DRG classifications. In 2007, the number of hospitals with PPS increased even more and most cantons used DRG classifications (see Meister, 2008). Unsurprisingly, in 2007 the Swiss parliament revised the insurance law to introduce a DRG system in all cantons by 2012. Following the U.S. Medicare reform of 1983 and the German reform of 2004, policy makers believe that the new reimbursement system would increase cost efficiency as outlined in the Introduction section. This article aims to determine whether the DRG system is preferable to contain health care costs. The hypotheses of interest are:

1. Hospitals with PPS are more cost efficient than hospitals with RPS. Putting a hospital at any amount of operating risk should strengthen incentives for cost minimization (lower cost inefficiency).
2. Hospitals with payments based on DRG classifications are more cost efficient than those paid with a per diem element. The fact that DRG systems do not account for longer length of stay should cause additional cost savings (lower cost inefficiency).

3. Estimation Models

In order to analyze these hypotheses, firm-specific inefficiency scores must first be established from estimated cost frontiers.³ This paper applies two specifications to check for the importance

³ See Coelli et al. (2005) and Kumbhakar and Lovell (2000) for an overview of inefficiency measurement methods.

of unobserved heterogeneity among hospitals. The first specification is a standard frontier model that was first implemented by Aigner et al. (1977) and Meeusen and van den Broeck (1977). It estimates inefficiency as the distance between a cost frontier and observed expenditures. Observable heterogeneity is captured by shifting means of the inefficiency term, similar to preliminary work by Battese and Coelli (1995), Huang and Liu (1994), and Kumbhakar et al. (1991). The second specification is a random parameter frontier model that additionally controls for unobserved heterogeneity in technology parameters (for other applications see Orea and Kumbhakar, 2004 and Tsionas, 2002). Inefficiency is estimated as cost deviations from category-specific cost frontiers.

3.1. The Standard Frontier Model (SFM)

The cost frontier for hospital $i = 1, \dots, N$ at time period $t = 1, \dots, T$ can be written as

$$C_{it} = C(Y_{it}, W_{it}; \alpha, \beta) + \overbrace{u_{it} + v_{it}}^{\varepsilon_{it}}, \quad (1)$$

with C_{it} representing operating expenditures, Y_{it} denoting the output vector, and W_{it} as the vector of input prices. α is the intercept and β is a $(K \times 1)$ vector of unknown slope parameters. $C(Y_{it}, W_{it}; \alpha, \beta)$ is the deterministic part of the cost frontier that remains to be specified for the empirical estimation. Typically, this is either a Cobb-Douglas or a more flexible translog functional form.

The error term ε_{it} is split into two additive components, enabling deviations for random noise, v_{it} and cost inefficiency, u_{it} . Random noise is normally distributed $v_{it} \stackrel{iid}{\sim} N[0, \sigma_v^2]$ with mean zero and variance σ_v^2 . Firm-specific inefficiency u_{it} is assumed to follow a one-sided distribution supported on the interval $[0, \infty)$. The larger u_{it} , the more cost inefficient a hospital and the greater the potential for cost savings.

Since the main purpose of this paper is to analyze the influence of PPS on inefficiency, inefficiency is specified congruent to Battese and Coelli (1995) as a truncated normal distribution $u_{it} \sim f_{N^+}[\bar{u}_{it}, \sigma_u^2]$ with firm specific means \bar{u}_{it} and variance σ_u^2 . In this article, mean inefficiency is a linear function of $l = 1, \dots, L$ explanatory variables Z_{lit} that influence inefficiency.

$$\bar{u}_{it} = \gamma_o + \sum_{l=1}^L \gamma_l Z_{lit} + \varsigma_{it}, \quad (2)$$

where γ is an $(L \times 1)$ vector of unknown parameters to be estimated and ς_{it} remains as unexplained hospital-specific inefficiency.

3.2. The Random Parameter Frontier Model (RPFM)

One way to extend the SFM for unobserved heterogeneity is the random parameter frontier model, which estimates inefficiency scores from individual cost frontiers.⁴ In this article, the model accounts for $j = 1, \dots, J$ exogenously given hospital categories that are expected to have different production technologies.

$$\begin{aligned}
 C_{it} &= C(Y_{it}, W_{it}; \alpha_j, \beta_j) + \overbrace{u_{it} + v_{it}}^{\varepsilon_{it}}, \\
 u_{it} &\sim f_{N^+}[\bar{u}_{it}, \sigma_u^2], \quad \bar{u}_{it} = \gamma_o + \sum_{l=1}^L \gamma_l Z_{lit} + S_{it}, \\
 \alpha_j &= \alpha + w_j, \\
 \beta_j &= \beta + w_j.
 \end{aligned} \tag{3}$$

Different from SFM, this specification allows inefficiency to be disentangled from unobservable heterogeneity with hospital category-specific intercepts $\alpha_j = \alpha + w_j$ and slope parameters $\beta_j = \beta + w_j$. All time-invariant and firm-specific heterogeneity is captured in w_j , which is a $[(K + 1) \times 1]$ vector of random variables.

This paper specifies α_j and β_j similar to Tsionas (2002) as a multivariate normal distribution

$$\begin{pmatrix} \alpha_j \\ \beta_j \end{pmatrix} \sim f_{MN} \left[\begin{pmatrix} \bar{\alpha} \\ \bar{\beta} \end{pmatrix}, \Sigma \right], \quad \text{with } \Sigma \sim f_W \begin{bmatrix} \sigma_\alpha^2 & \sigma_{\alpha,\beta} \\ \sigma_{\alpha,\beta} & \sigma_\beta^2 \end{bmatrix}, \tag{4}$$

where $\bar{\alpha} \sim N[0, \sigma_\alpha^2]$ and $\bar{\beta} \sim N[0, \sigma_\beta^2]$ are both normally distributed with mean zero and variance (σ_u^2, σ_v^2) . This is a hierarchical model that first measures the mean effects $(\bar{\alpha}, \bar{\beta})$ and then estimates individual effects (α_j, β_j) for each parameter. Variance Σ is Wishart distributed with a $[(K + 1) \times (K + 1)]$ positive definite covariance matrix $S = (\sigma_\alpha^2, \sigma_\beta^2, \sigma_{\alpha,\beta})$, denoting unobserved heterogeneity among hospitals. For $\Sigma = 0$ no variation exists and the RPFM simplifies to a SFM.

Based on the distributional assumptions made in the SFM and RPFM, Bayesian econometrics is applied for the simultaneous estimation of the parameters in the cost frontier and the inefficiency term. This is superior to the frequently applied classical maximum likelihood statistics since it considers unknown parameters as random variables, specified as prior distributions. Exact small sample results are possible because of the prior information included. Estimation is performed using

⁴ It is worth mentioning that a separation is not preferable in every case. If technology is manageable, defining of inefficiency on the frontier intercepts and ignoring the variation of the slope parameters could be justified. In this case, inferior technology is manageable inefficiency.

R and Winbugs. Corresponding Bayesian specifications and R programming codes are described in the Appendix.

4. Data and Econometric Specifications

4.1. The Sample

Data used in this study were provided by the annual reports of the federal office of public health and by the conference of cantonal health ministers. They include 333 Swiss hospitals for the time period of 2004 to 2009, consisting of 5 university hospitals, 23 central hospitals, 27 large regional hospitals, 46 medium regional hospitals, 46 small regional hospitals, 28 specialized surgery hospitals, and sundry hospitals, viz. psychiatric and rehabilitation clinics. In total, 127 of the 333 hospitals are private and not subsidized.

In the interest of comparability, the entire data set was reviewed and assessed for the presence of any missing data and outliers that could distort the results. Furthermore, the sundry category and all non-subsidized hospitals were discarded. An unbalanced panel consisting of 545 observations from six different hospital categories with sufficient was finally analyzed. In Table 1, the variables are listed together with descriptive statistics.

Table 1: Definition and Descriptive Statistics of the Variables Used in the Analysis

Variable	Definition	Mean	Min	Max
VC	Variable operational expense, in thousands of CHF (VC) ¹⁾	135,621	8,550	1,015,756
Y_1	No. of inpatient cases, CMI-adj. ($CASES$)	9,113	502	52,143
Y_2	Revenue from outpatients, in thousands of CHF ($OUTP$) ¹⁾	27,418	0	223,937
PL	Labor input price, in thousands of CHF (PL) ¹⁾	101	34	146
PM	Price of other production inputs, in thousands of CHF (PM) ¹⁾	4	2	7
K	No. of beds ($BEDS$)	229	31	1,169
S_1	No. of internship categories ($INTERN$)	22	0	134
S_2	No. of specialties ($SPEC$)	39	4	106
Z_1	Dummy= 1 for prospective payment systems (PPS) ²⁾	78	0	100
Z_2	Dummy= 1 for payments per patient case ($CASEP$) ²⁾	14	0	100
Z_3	Dummy= 1 for global budgets ($GLOB$) ²⁾	64	0	100
Z_4	Dummy= 1 for DRG classifications (DRG) ²⁾	51	0	100
T_t	Year dummies, $t = 2005$ to 2009 (base year is 2004)			

¹⁾ in 1,000 CHF, 1 CHF=0.8 USD (2004 exchange rates)

²⁾ in percent, PPS=78 in column three means that on average 78 percent of all hospitals have PPS

4.2. Specification of the Cost Frontier

With these data, a variable Cobb-Douglas cost frontier (subscripts $i = 1, \dots, N$ and $t = 1, \dots, T$ are dropped for simplicity) can be specified as

$$\ln \frac{VC}{PM} = \alpha + \sum_{m=1}^2 \beta_m \ln Y_m + \beta_3 \ln \frac{PL}{PM} + \beta_4 \ln K_4 + \sum_{l=1}^2 \beta_l S_l + \sum_{t=1}^5 \beta_t T_t + u + v, \quad (5)$$

where variable cost (VC) depends on two output categories (Y), one input price for labor (PL), one price for other production inputs (PM), one capital stock (K), two structural variables (S), and five time dummies (T) to control for any unobserved dynamics over time (base year 2004). Normalizing VC and PL by PM imposes linear homogeneity in input prices.

Health care output – change in health status – is difficult to measure directly for Swiss hospitals. In this article, measures for inpatient care $CASES$ and outpatient care $OUTP$ serve as intermediate outputs. To adjust for severity in inpatient care, CMI-adjusted admissions are used. Outpatient care is approximated by ambulatory earnings, similar to Farsi et al. (2006) and Biorn et al. (2003). Furthermore, input price PL is calculated as labor expense divided by the number of full time employees. Input price PM aggregates all the remaining inputs, such as energy, material, and purchased services that cannot be distinguished due to data limitations. An approximate price for PM is calculated as residual cost divided by the number of admissions (a discussion of this common simplification is given in Coelli et al., 2005, p.141). Since capital stock (total fixed assets) is hardly measurable, $BEDS$ serve as an approximation. Finally, the number of internship categories $INTERN$ and specialties $SPEC$ control for observable service heterogeneity among hospitals.

The formulation can be justified on several grounds. First, it is compatible with short-term cost minimization, reflecting the fact that capital (indicated by $BEDS$) is a predetermined rather than a decision variable. In Switzerland, cantonal hospital planning divisions mainly decide capacity. Second, the exclusion of user cost of capital from the equation avoids measurement errors since values would have to be imputed since most hospitals are not charged capital user costs.

4.3. Determinants of Inefficiency

Since the influence of PPS on inefficiency is the focus of this article, additional explanatory variables are included in the inefficiency term – see eq. (2) – to test for the two hypotheses from Section 2:

- (1) Hospitals with PPS are more cost efficient than hospitals with RPS;

(2) Hospitals with payments based on DRG classifications are more cost efficient than those paid with a per diem element.

Hypothesis (1) is tested with two models. Model (1) refers to eq. (6),

$$\bar{u}_{it} = \gamma_o + \gamma_1 PPS + \gamma_2 PPS:DRG + \varsigma_{it}, \quad (6)$$

which relates mean inefficiency to a dummy variable that equals one for hospitals with PPS and zero for hospitals with RPS. It determines whether PPS – either a global budget or a payment per patient case system – is more effective than the retrospective alternative.

Model (2) refers to eq. (7),

$$\bar{u}_{it} = \gamma_o + \gamma_1 CASEP + \gamma_2 GLOB + \gamma_3 CASEP:DRG + \gamma_4 GLOB:DRG + \varsigma_{it}, \quad (7)$$

which is a refinement of Model (1) that checks for the unique effects of a global budget and a payment per patient case system. Therefore, the variable PPS is replaced by two dummy variables, *GLOB*, for hospitals with a global budget, and *CASEP*, for hospitals with payments per patient case. Hospitals with a retrospective per diem system form the control group. In Model (2), it is expected (from Section 2) that hospitals receiving payments per patient case are more cost efficient (have lower inefficiency scores) since most hospitals with global budgets have a partial deficit guaranty through the opportunity to adjust their budgets for unexpected costs.

Hypothesis (2) calls for the introduction of an additional dummy variable, *DRG*, in eqs. (6) and (7), which is specified as a nested interaction term. It measures the supplementary effect of DRG classifications relative to the alternative specification with a per diem element. As outlined in Section 2, payments based on a per diem element can reduce incentives for cost minimization since hospitals have incentive to increase the length of stay. Therefore, it is expected that hospitals with DRG, which is free from any adjustment for length of stay, are more efficient (have lower inefficiency scores) than the frequently applied alternative.

Finally, Model (3) refers to eq. (8),

$$\bar{u}_{it} = \gamma_o + \gamma_1 PPS + \gamma_2 PPS:DRG + \gamma_3 PPS:DRG_1 + \gamma_4 PPS:DRG_2 + \varsigma_{it}, \quad (8)$$

which refines Model (1) for a possible catch-up effect of DRG over time. Therefore, two additional dummies DRG_j , $j = 1, 2$ are included, where j indicates the time lag from the initiation of the reimbursement scheme. Since it is possible that DRG only becomes effective after a few years after

initiation, it is preferable to test for these effects as well.

5. Empirical Results

This section first presents estimates of the technology parameters and inefficiency scores with a special focus on the influence of unobserved heterogeneity. Second, in Section 5.2, the influence of PPS is discussed for the three models outlined in Section 4.3.

To obtain posterior estimates, Monte Carlo Markov Chain (MCMC) algorithms were run for 20,000 iterations and the first 10,000 samples were discarded as a burn-in phase. Different assumptions for priors and starting values converged to roughly the same values without strong periodicities or tendencies in the trace plot. Furthermore, the Monte Carlo error is very low. All cost frontier parameters and inefficiency scores have a Monte Carlo error lower than $7.02 * 10^{-4}$, indicating that the results are quite precise and have reached the equilibrium distribution.

5.1. Cost Frontier Estimates and Their Inefficiency Scores

Table 2 shows the estimates of the technology parameters of the the variable cost frontier from eq. (5) after an analysis of cost drivers together with tests for endogeneity, heteroscedasticity, and the skewness of the composite error term were performed. Hospital output could be endogenous in the RPS when hospitals have incentive to increase their output due to higher remuneration. However, a Hausman test did not suggest rejection of the exogeneity assumption. Heteroscedasticity was also not problem according to a Breusch-Pagan test. Only *INTERN* had a weak effect on the variance of the composite error term. Finally, because inefficient hospitals by definition lie above the cost frontier, a positively skewed composite error term is required for efficiency measurement. Otherwise, no inefficiency would exist and OLS would be sufficient to estimate the cost frontier. However, residuals of the cost driver analysis were positively skewed, indicating that inefficiency does exist in the Swiss hospital sector.

In the SFM, the first three columns contain the estimation mean, the 2.5, and 97.5 percentile of the technology parameters. They satisfy economic conditions in that the cost frontier monotonically increases in the outputs *CASES* and *OUTP* as well as in the input price *PL*. The only exception is hospital beds (*BEDS* = 0.22). Since it is an indicator of capital stock, it should have a negative sign (see Kumbhakar and Lovell, 2000). However, because hospital capacity (no. of hospital beds) is exogenously determined by the cantonal authority, the expected substitution effect could be very small. Furthermore, because *BEDS* is a poor proxy for capital stock, which is highly correlated with hospital output, estimates might show an output rather than a substitution effect (see e.g. Fil-

ippini et al., 2004 for similar difficulties). Consequently, an investigation of the shadow price is not possible, but inefficiency scores are still derivable. Moreover, variable costs tend to shift up systematically over time, with a maximum in 2009 ($T_{09} = 0.036$). Finally, with regard to service heterogeneity it is not surprising that internship categories ($INTERN = 0.002$) and the number of specialties ($SPEC = 0.001$) have a positive effect. Variable cost increases with the number of different services offered.

Table 2: Econometric Results for the SFM and RPFM, Years 2004 to 2009

Variables ¹⁾	SFM			RPFM			
	Mean	2.50%	97.50%	Mean	2.50%	97.50%	SD
<i>Constant</i>	-0.088	-0.103	-0.073	-0.123	-0.201	-0.059	0.074
<i>CASES</i>	0.744	0.708	0.781	0.592	0.359	0.768	0.224
<i>OUTP</i>	0.004	-0.002	0.011	0.076	-0.045	0.217	0.158
<i>PL</i>	0.382	0.347	0.418	0.434	0.286	0.612	0.169
<i>BEDS</i>	0.220	0.182	0.258	0.281	0.118	0.482	0.159
<i>INTERN</i>	0.002	0.001	0.002	0.000	-0.001	0.002	0.001
<i>SPEC</i>	0.001	0.000	0.002	0.001	0.000	0.002	0.001
T_{09}	0.036	0.008	0.065	0.017	-0.014	0.045	0.019
T_{08}	0.023	-0.005	0.051	0.007	-0.013	0.031	0.009
T_{07}	0.012	-0.016	0.040	0.002	-0.016	0.024	0.008
T_{06}	0.023	-0.005	0.051	0.009	-0.011	0.032	0.009
T_{05}	0.009	-0.017	0.034	0.004	-0.015	0.028	0.011
σ_u	0.013	0.009	0.017	0.001	0.000	0.003	
σ_v	0.004	0.003	0.006	0.003	0.002	0.004	
<i>DIC</i>	-1106			-1596			
Obs.	545			545			

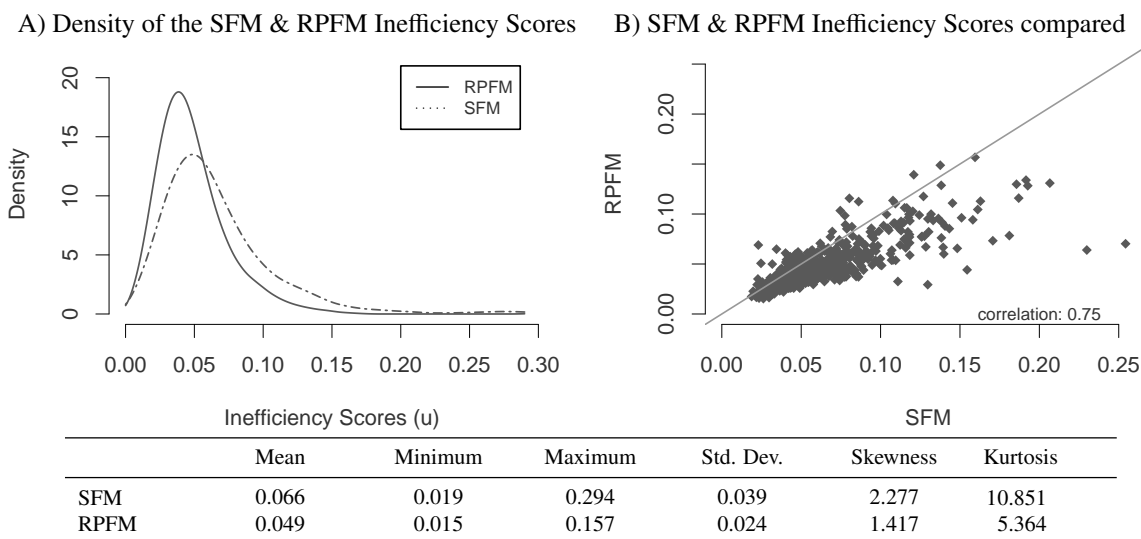
¹⁾ Variable cost (VC) is the dependent variable. Determinants of inefficiency are shown separately in Table 3

Estimates for the RPFM only have slightly different values [estimation means are represented by $\bar{\beta}$ of eq. (4)]. However, the results in the last column suggest that there is a fair amount of variation in the frontier model parameters. Estimates reveal the diagonal of the covariance matrix Σ of eq. (4), which can be interpreted as the variation in the parameters across hospital categories. Heterogeneity is highest for inpatient care ($CASES = 0.224$), followed by the input price for labor ($PL = 0.169$), capital stock ($BEDS = 0.159$), and outpatient care ($OUTP = 0.158$). It is remarkable that even though heterogeneity in inpatient care is already adjusted for by a casemix index, indisputable variation remains among hospital categories. This raises doubts about the relevance of the DRG classifications to control for cost variability in inpatient care. However, in order to determine whether the greater flexibility of the RPFM is indicated by the data, both models are assessed by the DIC information criteria shown in Table 2 (Spiegelhalter et al., 2002). The lower the DIC-value, the better the goodness of fit of the estimated cost frontier, indicating that the RPFM ($DIC = -1596$) has better fit than the SFM ($DIC = -1106$). The SFM seems to be too restrictive for Switzerland.

More flexible variants are needed to capture all the existing heterogeneity among hospital categories.

For the present study, the more important question is the impact of unobserved heterogeneity on the estimated inefficiency scores. As shown by Widmer et al. (2010), unmeasured heterogeneity can masquerade as inefficiency u_{it} . This is shown in the scatter and density plots in Figures 2 and 3. Figure 2 shows the inefficiency scores of the SFM and the RPFM. Figure 3 presents preliminary indications of the influence of PPS.

Figure 2: Estimated Inefficiency Scores of the SFM and RPFM, Years 2004-9



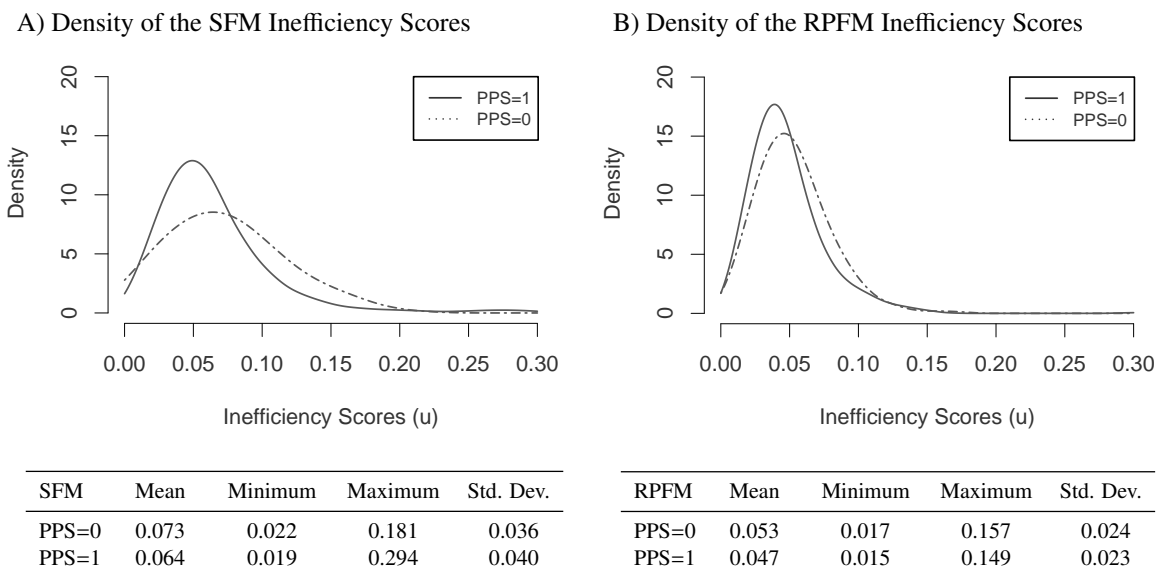
There are strong differences across the two models. Unobserved heterogeneity increases estimated inefficiency scores, potentially resulting in the overstatement of cost reduction (Figure 2 panel A). The mean inefficiency score of the SFM is 0.066, meaning that Swiss hospitals could on average reduce 7 percent of their variable costs. However, using the RPFM, mean inefficiency reduces to about 5 percent. Approximately 2 percent of the SFM scores can be detected as unobserved heterogeneity. A comparison of the individual scores in panel B is even more revealing. Although both models have a high correlation of 0.75, hospitals are systematically measured as more inefficient in the SFM. In particular, hospitals that would have been rated highly inefficient in the SFM gain ground when the RPFM is applied. The maximum inefficiency score decreases from 0.294 for the SFM to 0.157 for the RPFM, putting the maximum cost reduction at about 16 percent. At a given point in time and for the majority of Swiss hospitals, it clearly matters whether or not unobserved heterogeneity is taken into account.

At this point, it is noteworthy that even the SFM reveals a significant smaller potential for cost reduction than previous studies to the Swiss hospital sector, such as in Widmer et al. (2010), Farsi and Filippini (2006), and Steinmann and Zweifel (2003). However, since only a subsample of public

financed Swiss hospitals is used here, results can not directly be compared.

Next, it is of interest to determine whether unobserved heterogeneity biases inferences on inefficiency scores as well. A preliminary indication is given in Figure 3 for the effectiveness of PPS.

Figure 3: Estimated Inefficiency Scores by Model Type, Year 2004-9



Surprisingly, even though SFM scores are indisputably biased, both models come up with comparable conclusions that PPS reduces hospital cost inefficiency. In the SFM, mean inefficiency decreases from 0.073 to 0.064 (Figure 3 panel A). In the RPFM, mean inefficiency scores decrease from 0.053 to 0.047 (Figure 3 panel B). Both reductions are significant according to a Wilcoxon rank sum test (the hypothesis that mean inefficiency is equal for the two groups can be rejected at the 95 confidence level). However, the decrease in inefficiency is larger in the SFM (mean = -0.009) than in the RPFM (mean = -0.006), with a favor for the RPFM.

It is also worth noting at this point that because heterogeneity is specified as a time-invariant random variable, time-invariant inefficiency could be misleadingly estimated as heterogeneity in the RPFM as well. Thus, estimates of the inefficiency scores could be negatively biased, putting the true influence of PPS on inefficiency somewhere in between the two cost frontier specifications.

5.2. Sources of Inefficiency

Given the encouraging results in the preceding section, further analysis of the influence of PPS on inefficiency is warranted. Table 3 presents estimation results for the three models outlined in Section 4.3. The dependent variable is the mean inefficiency \bar{u}_{it} of eq. (2). All results are estimated

together with the parameters of the cost frontier, shown in Table 2 for Model (1).⁵

Table 3: Determinants of Inefficiency by Model Type, Years 2004-9

Variables ¹⁾	SFM			RPFM		
	Mean	2.5%	97.5%	Mean	2.5%	97.5%
Model 1:						
Constant	-0.13	-0.31	0.01	-0.17	-0.35	-0.04
PPS	0.02	-0.09	0.12	-0.01	-0.15	0.09
PPS:DRG	-0.15	-0.31	-0.04	-0.08	-0.22	0.02
Model 2:						
Constant	-0.15	-0.35	-0.01	-0.17	-0.33	-0.05
CASEP	-0.08	-0.30	0.13	-0.07	-0.26	0.11
GLOB	0.03	-0.07	0.14	0.00	-0.13	0.10
CASEP:DRG	-0.06	-0.29	0.14	-0.04	-0.24	0.15
GLOB:DRG	-0.15	-0.32	-0.03	-0.07	-0.22	0.03
Model 3:						
Constant	-0.16	-0.36	-0.03	-0.19	-0.36	-0.06
PPS	0.02	-0.11	0.13	-0.02	-0.16	0.09
PPS:DRG	-0.13	-0.33	0.03	-0.08	-0.25	0.07
PPS:DRG1	-0.08	-0.29	0.10	-0.03	-0.21	0.14
PPS:DRG2	-0.01	-0.25	0.18	-0.02	-0.19	0.15

¹⁾ Mean inefficiency \bar{u}_{it} is the dependent variable in each model. Technology parameters are dropped for simplicity; those of Model (1) are shown in Table 2

In Model (1), an unexpected positive sign is obtained for *PPS* in the SFM (mean = 0.02), indicating that *PPS* increases hospital inefficiency. In contrast, the more appropriate RPFM shows a small negative value (mean = -0.01). This is rather counterintuitive, suggesting that unobserved heterogeneity substantively biases estimates of the influence of *PPS* on inefficiency. Yet, a 1 percent decrease in inefficiency remains after controlling for unobserved heterogeneity. Estimates for the interaction term *PPS:DRG* are more intuitive. In both cases, *DRG* is negatively correlated with hospital inefficiency. However, the effect is unreasonably large in the SFM (mean = -0.15). Estimates for Model (2) are similar. Although both approaches have comparable signs, estimates for *GLOB* and *GLOB:DRG* differ significantly between the two approaches. In the SFM, *GLOB* is found to have a positive influence (mean = 0.03) on inefficiency and no effect in the RPFM (mean = 0.00). Moreover, the interaction term indicates an unreasonably high negative effect (mean = -0.15) in the SFM. Even in Model (3), which controls for a possible time-lag of *DRG*, the estimated effects are systematically larger in the SFM and again *PPS* seems to be significantly biased by unobserved heterogeneity. Taken together, estimation results are less robust between the SFM and RPFM than expected. The results mainly depend on the assumptions made to the production technology.

⁵ Technology parameters of Model (2) and (3) are not shown. They are found to be comparable to those discussed in Section 5.1.

Nevertheless, RPS appears to undermine efforts for cost containment, addressing hypothesis (1). Inefficiency decreases by about -0.01 for hospitals with PPS, meaning that a switch to PPS causes hospitals to reduce their variable costs by an average of 1 percent. However, as shown in Model (2), efficiency gains depend substantially on whether hospitals are paid by a global budget or receive payments per patient case. While a payment per patient case system reduces hospital-specific inefficiency by about -0.07 on average, no efficiency gains occur with a global budget system (in the biased SFM they are even more inefficient, 0.03). The renegotiations that most cantons still allow of the global budget at the end of the accounting period seem to reduce incentives for cost minimization. Hospital managers may anticipate that additional financial support will be given for unexpected operating cost.

While general remuneration settings per admission, which include a per diem element, can induce hospitals to treat patients too long, a DRG system increases the incentive for a shorter length of stay. As estimates from Table 3 show, this results in lower cost inefficiency for hospitals with a DRG system, addressing hypothesis (2). Model (2), which shows the unique effects of *DRG* for hospitals with a global budget and payments per patient case system, revealed that the efficiency gains of *DRG* are even larger in the global budget (-0.07) than in the payment per patient case system (-0.04). However, the combined effect of the payment per patient case system is larger ($-0.11 = -0.07 - 0.04$) than the expected cost savings under a global budget system ($-0.07 = 0.00 - 0.07$), making the payment per patient case system together with DRG classifications the preferable variant for Switzerland. Under a payment per patient case system with DRG classifications, hospitals have 11 percent lower inefficiency scores on average than their counterparts with RPS. Moreover, Model (3) reveals that a DRG system is not fully effective in the first year after initiation. Although most cost savings occur in the first year ($DRG = -0.08$), additional reduction is observable in the second ($DRG_1 = -0.03$) and third year ($DRG_2 = -0.02$) after implementation.

Finally, these findings are in line with the theoretical expectations, for example outlined in Chalkley and Malcomson (2000) and Newhouse (1996). With respect to the hospital payment reform becoming effective in 2012, these results support the policy expectations that PPS will rather increase cost efficiency. However, the implementation has to be fully prospective and preclude any bailouts.

6. Concluding Remarks

The purpose of this article was to estimate the effectiveness of prospective payment systems in reducing hospital cost inefficiency. Hospitals in Switzerland are analyzed, which, in contrast to previous studies, enables a comparison of a retrospective per diem system with two prospective

payment systems, one based on a global budget and other based on payments per patient case. Since the results of previous studies may have been affected by the existence of unobserved heterogeneity, two stochastic frontier models are used to control for potential bias. The first is a standard frontier model (SFM) that assumes a homogeneous technology for all hospitals. The second one is a random parameter frontier model (RPFM) that controls for unobserved heterogeneity with hospital group-specific intercepts and slope parameters. A variable cost frontier is estimated for approximately 90 public financed Swiss hospitals during the time period of 2004 to 2009.

There are two main results from this analysis. First, a comparison of the standard and random parameter frontier models reveals that heterogeneity is substantial between Swiss hospital categories. Inefficiency scores are biased upwards by two percent on average in the SFM. The maximum inefficiency score decreases from 0.294 in the SFM to 0.157 in the RPFM, putting the maximum cost savings at approximately 16 percent. Further analysis of the determinants of inefficiency shows that unobserved heterogeneity systematically varies among hospitals, indicating that the SFM is not able to detect the true effect of prospective payment systems on inefficiency. The assumptions made for the production technology (SFM vs. RPFM) are important in the Swiss case.

Second, prospective payment systems are associated with an increase in hospital cost efficiency, particularly for the payment per patient case system. Payment systems designed to put hospitals at operating risk seem to be more effective in reducing hospital costs than retrospective payment systems. However, these effects may be diminished if cantons do not firmly preclude a bailout. Results relating to the global budget system reveal that if hospitals can obtain higher budgets to cover past errors, then the incentive for cost minimization disappears. In addition, the settings for the remuneration per admission are also important. Whereas general remuneration settings with a per diem element can be used to unnecessarily keep a patient in the hospital, a DRG system strengthens incentives for cost minimization. Nonetheless, estimates show that DRG is not fully effective after initiation. Additional efficiency gains occur later on, although these are smaller in the third year than in the second year. Therefore, these empirical findings are in line with the theoretical expectations. With respect to the hospital payment reform effective in 2012, these results support the expectations of Swiss politicians that the new payment system can contain health care costs. However, the implementation has to be fully prospective and has to preclude any bailouts.

This analysis is not without limitations. Above all, unobserved heterogeneity is estimated as a time-invariant random variable, meaning that all time-invariant random noise is measured as heterogeneity. Since inefficiency could be time-invariant as well, estimates to the RPFM underestimate inefficiency. Nevertheless, together with the SFM, which overestimates inefficiency, the true influence

of PPS must lie somewhere between, making the results still reliable. Additionally, a translog form would have been more accurate than the Cobb-Douglas form for the production technology since it can test for specific features of technology (like economies of scale or homotheticity) by examining the estimated model parameters. Unfortunately, limitations of the data dictated the application of the reduced self-dual Cobb-Douglas form, which per definition is restricted to constant elasticities of substitution and is constant in economies of scale. Thus, estimates might be biased in cases when these assumptions are not reasonable. In spite of this limitation, the analysis not only identifies the effect of PPS on inefficiency, it also outlines the importance of unobserved heterogeneity in deriving unbiased inefficiency scores.

Appendix: The Bayesian Specification

This paper uses Bayesian statistics to estimate eqs. (1) and (3). Inference is made from a posterior distribution $p(\theta|X)$ of the unknown parameters (summarized as θ) given the observed data (summarized as X). According to the Bayesian rule this is

$$p(\theta|X) = \frac{\mathcal{L}(X|\theta)p(\theta)}{p(X)} \propto p(\theta)\mathcal{L}(X|\theta), \quad (9)$$

expressed as the product of the prior information $p(\theta)$ and the likelihood $\mathcal{L}(X|\theta)$, respectively.

For the estimates in Section 5, the posterior distribution for the SFM is specified as

$$\begin{aligned} p(\alpha, \beta, u, \gamma, \sigma_v^{-2}, \sigma_u^{-2}; C, Y, W, Z) &\propto p(\alpha, \beta, \gamma, \sigma_v^{-2}, \sigma_u^{-2}) \prod_{i=1}^N \prod_{t=1}^T p(u, \gamma, \sigma_u^{-2}|Z) \\ &\times \prod_{i=1}^N \prod_{t=1}^T \frac{1}{\sqrt{2\pi\sigma_v^2}} \exp\left[-\frac{1}{2\sigma_v^2} (C_{it} - [C(Y_{it}, W_{it}; \alpha, \beta) + u_{it}])^2\right], \quad (10) \end{aligned}$$

where $p(\alpha, \beta, \gamma, \sigma_v^{-2}, \sigma_u^{-2})$ are probability distributions of the unknown parameters. The likelihood function in eq. (10) is as in Griffin and Steel (2007), normally distributed with σ_v^2 as the variance of the random noise $v_{it} = C_{it} - [C(Y_{it}, W_{it}; \alpha, \beta) + u_{it}]$. This is a gain in flexibility over classical maximum likelihood applications, where a joint density function of the random noise and the inefficiency term is specified. Here, only random noise enters the likelihood function. Inefficiency is estimated hierarchically as a latent variable along with the other parameters of the cost frontier.

Turning to the RPFM the posterior is given by

$$\begin{aligned} p(\alpha, \bar{\alpha}, \beta, \bar{\beta}, u, \gamma, \Sigma, \sigma_v^{-2}, \sigma_u^{-2}; C, Y, W, Z) &\propto p(\bar{\alpha}, \bar{\beta}, \gamma, \Sigma, \sigma_v^{-2}, \sigma_u^{-2}) \prod_{i=1}^N \prod_{t=1}^T p(u, \gamma, \sigma_u^{-2}|Z) \\ &\times \prod_{j=1}^J (2\pi)^{-K/2} |\Sigma|^{-1/2} \exp\left[-\frac{1}{2} \left(\begin{pmatrix} \alpha_j \\ \beta_j \end{pmatrix} - \begin{pmatrix} \bar{\alpha} \\ \bar{\beta} \end{pmatrix} \right)' \Sigma^{-1} \left(\begin{pmatrix} \alpha_j \\ \beta_j \end{pmatrix} - \begin{pmatrix} \bar{\alpha} \\ \bar{\beta} \end{pmatrix} \right)\right] \\ &\times \prod_{i=1}^N \prod_{t=1}^T \frac{1}{\sqrt{2\pi\sigma_v^2}} \exp\left[-\frac{1}{2\sigma_v^2} (C_{it} - [C(Y_{it}, W_{it}; \alpha_j, \beta_j) + u_{it}])^2\right]. \quad (11) \end{aligned}$$

Again, the likelihood function is specified as a normal distribution and inefficiency is estimated as a latent variable together with the other unknown parameters. Different is the specification of the random intercept α_j and the slope parameters β_j , which are estimated at two levels. At the first level, overall influences on hospital cost ($\bar{\alpha}, \bar{\beta}$) are determined, corresponding to the first factor following the proportionally sign of eq. (11). The second-level estimates of the individual effects (α_j, β_j) defined in eq. (4) are derived from the multivariate normal distribution shown in eq. (11).

In contrast to classical statistics, an application of Bayesian statistics requires additional information for the prior distributions of the unknown parameters, since all parameters are considered as random variables. They should comprise all information available before any data are involved in the statistical analysis. In this case, the values for the hyperparameters are chosen in a way to imply relatively vague but proper priors. In particular, the priors for the SFM and RPFM are assumed to be independent,

$$p(\alpha, \beta, \gamma, \sigma_v^{-2}, \sigma_u^{-2}) = p(\alpha), p(\beta), p(\gamma), p(\sigma_v^{-2}), p(\sigma_u^{-2}) \quad (12)$$

$$p(\bar{\alpha}, \bar{\beta}, \gamma, \Sigma, \sigma_v^{-2}, \sigma_u^{-2}) = p(\bar{\alpha}), p(\bar{\beta}), p(\gamma), p(\Sigma), p(\sigma_v^{-2}), p(\sigma_u^{-2}) \quad (13)$$

Here, $p(\alpha) = f_N[0, \theta_\alpha]$, $p(\bar{\alpha}) = f_N[0, \theta_{\bar{\alpha}}]$, $p(\beta) = f_N[0, \theta_\beta]$, $p(\bar{\beta}) = f_N[0, \theta_{\bar{\beta}}]$ have a normal distribution with mean zero and a diffuse prior for their corresponding variance θ . The variance of the likelihood function has a gamma distribution $p(\sigma_v^{-2}) = f_G[\mu, \theta_{\sigma_v^{-2}}]$ with diffuse shape and scale parameters. Inefficiency is assumed to be truncated normally distributed $p(u, \gamma, \sigma_u^2 | Z) = f_N^+[\gamma Z, \sigma_u^2]$ with $\sigma_u^2 = f_G[5, (5 * \log(\bar{r})^2)]$ and $p(\gamma) = f_N[0, \theta_\gamma] / \sqrt{f_G[5, (5 * \log(\bar{r})^2)]}$. This specification is in line with Griffin and Steel (2007) and Koop et al. (1997), permitting to impose a priori information with regard to mean efficiency, $\overline{eff} = \exp(-\bar{u})$. Following the formulation of Griffin and Steel (2007), $\overline{eff} = 0.875$ is assumed for prior efficiency. Finally, the variance of the random parameters is specified as a Wishart distribution $p(\Sigma) = f_W[S]$ in accordance with Eq. 11 with diffuse prior for the covariance matrix S .

Finally, note that estimates of the unknown parameters can be derived by the marginal posteriors of eqs. (10) and (11). However, it is not always possible to compute the posteriors analytically. Therefore, iterative Monte Carlo Markov Chain (MCMC) simulation is used, which involves iterative sampling from posterior parameter densities. Here, we use WINBUGS to derive the estimates (see Ntzoufras, 2009 for an introduction). The corresponding computational codes for the SFM and RPFM are shown in Table 4.

Table 4: Computation codes for the standard frontier and the random parameter frontier model with truncated normal distributed efficiency scores

Standard Frontier Model	Random Parameter Frontier Model
<pre> model{ for (it in 1:NT){ firm[it] ← n[it,1] Likelihood: Y[it] ~ dnorm(mu[it], prec) mu[it] ← inprod(b[1:K+1], X[it, 1:K+1]) + u[firm[it]] } Hyperpriors: for (it in 1:NT) { u[it] ~ djl.dnorm.trunc(mu1[it],lambda,0,1000) mu1[it] ← inprod(t[1:L+1], Z[it,1:L+1]) } Priors: for (k in 1:K+1) { b[k] ~ dnorm(0, 0.0001) } for(l in 1:L+1){ t[l] ← gamma[l] / sqrt(lambda) gamma[l] ~ dnorm(0.0, 1) } lambda0 ← 5*log(\bar{r})*log(\bar{r}) lambda ~ dgamma(5,lambda0) prec ~ dgamma(0.1,0.01) </pre>	<pre> model{ for(it in 1:NT){ firm[it] ← n[it,1] typ[it] ← n[it,3] Likelihood: Y[it] ~ dnorm(mu[it], prec) mu[it] ← inprod(b[typ[it],1:K+1], X[it,1:K+1]) + u[firm[it]] } Hyperpriors: for (it in 1:NT) { u[it] ~ djl.dnorm.trunc(mu1[it],lambda,0,1000) mu1[it] ← inprod(t[1:L+1], Z[it,1:L+1]) } for(j in 1:J){ for(k in 1:K+1){ b[j,k]← xi.b[j]*b.raw[j,k] } b.raw[j,1:K+1] ~ dmnorm(b.bar.raw[],b.tau.raw[,j]) } Priors: for(k in 1:K+1){ b.bar[k] ← xi.b[k]*b.bar.raw[k] b.bar.raw[k] ~ dnorm(0,0.0001) xi.b[k] ~ dunif(-10,10) } for(l in 1:L+1){ t[l] ← gamma[l] / sqrt(lambda) gamma[l] ~ dnorm(0.0, 1) } lambda0 ← 5 * log(\bar{r}) * log(\bar{r}) lambda ~ dgamma(5,lambda0) prec ~ dgamma(0.1,0.01) b.tau.raw[1:K+1,1:K+1] ~ dwish(S[1:K+1, 1:K+1], nu) nu ← K+1 Sigma.B.raw[1:K+1,1:K+1] ← Inverse (b.tau.raw[,j]) for(k in 1:K+1){ Sigma.B[k] ← abs(xi.b[k])* sqrt(Sigma.B.raw[,j]) } </pre>

References

- Aigner, D., Lovell, C. A. K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6 (1), 21–37.
- Battese, G. E., Coelli, T. J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics* 20 (2), 325–32.
- Biorn, E., Hagen, T., Iversen, T., Magnussen, J., 2003. The effect of activity-based financing on hospital efficiency: A panel data analysis of DEA efficiency scores 1992-2000. *Health Care Management Science* 6, 271–283.
- Biorn, E., Hagen, T. P., Iversen, T., Magnussen, J., 2006. Heterogeneity in hospitals' responses to a financial reform: A random coefficient analysis of the impact of activity-based financing on efficiency. Working Paper 8100, University Library of Munich, Germany.
- Borden, J. P., 1988. An assessment of the impact of diagnosis-related group (DRG)-based reimbursement on the technical efficiency of New Jersey hospitals using data envelopment analysis. *Journal of Accounting and Public Policy* 7 (2), 77 – 96.
- Chalkley, M., Malcomson, J. M., 1998. Contracting for health services when patient demand does not reflect quality. *Journal of Health Economics* 17 (1), 1–19.
- Chalkley, M., Malcomson, J. M., 2000. Government purchasing for health services. In: Culyer, A. J., Newhouse, J. P. (Eds.), *Handbook of Health Economics*. Vol. 1A. Elsevier Science Ltd, Amsterdam: North Holland, pp. 847–889.
- Chern, J.-Y., Wan, T. T. H., 2000. The impact of the prospective payment system on the technical efficiency of hospitals. *Journal of Medical Systems* 24, 159–172.
- Coelli, T., Rao, D. S. P., O'Donnell, C. J., Battese, G. E., 2005. *An Introduction to Efficiency and Productivity Analysis*. Springer.
- Dismuke, C., Sena, V., 1999. Has the DRG system influenced the efficiency of diagnostic technology in Portugal? an empirical analysis using parametric and non-parametric methods. *Health care management science* 2, 107–116.
- Farsi, M., Filippini, M., 2006. An analysis of efficiency and productivity in Swiss hospitals. *Swiss Journal of Economics and Statistics (SJES)* 142 (I), 1–37.
- Farsi, M., Filippini, M., Greene, W., 2006. Application of panel data models in benchmarking analysis of the electricity distribution sector. *Annals of Public and Cooperative Economics* 77 (3), 271–290.
- Filippini, M., Farsi, M., Crivelli, L., Zola, M., 2004. An analysis of efficiency and productivity in Swiss hospitals. Report, Swiss Federal Statistical Office.
- Griffin, J., Steel, M., 2007. Bayesian stochastic frontier analysis using WinBUGS. *Journal of Productivity Analysis* 27, 163–176.
- Huang, C., Liu, J., 1994. Estimation of a non-neutral stochastic frontier production function. *Journal of Productivity Analysis* 5, 68–80.
- Koop, G., Osiewalski, J., Steel, M. F. J., 1997. Bayesian efficiency analysis through individual effects: Hospital cost frontiers. *Journal of Econometrics* 76 (1-2), 77–105.

- Kumbhakar, S., Lovell, C. A. K., 2000. *Stochastic Frontier Analysis: An Econometric Approach*. Cambridge University Press, Cambridge.
- Kumbhakar, S. C., Ghosh, S., McGuckin, J. T., 1991. A generalized production frontier approach for estimating determinants of inefficiency in U.S. dairy farms. *Journal of Business & Economic Statistics* 9 (3), 279–86.
- Linna, M., 1999. The impact of health care financing reform on the productivity change in Finnish hospitals. *System Analysis Laboratory Research Reports* 79 (A).
- Meeusen, W., van den Broeck, J., 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review* 18 (2), 435–44.
- Meister, U., 2008. *Hospitals between regulation and competition (Spitäler zwischen Politik und Wettbewerb: Betriebliche Autonomie im Kantonsvergleich)*. Report, Avenir Suisse.
- Morey, R., Dittman, D., 1996. Cost pass-through reimbursement to hospitals and their impacts on operating efficiencies. *Annals of Operations Research* 67, 117–139.
- Newhouse, J. P., 1996. Reimbursing health plans and health providers: Efficiency in production versus selection. *Journal of Economic Literature* 34 (3), 1236–1263.
- Ntzoufras, I., 2009. *Bayesian modeling using WinBUGS*. Wiley Series in Computational Statistics. Wiley, Hoboken, NJ.
- Orea, L., Kumbhakar, S. C., 2004. Efficiency measurement using a latent class stochastic frontier model. *Empirical Economics* 29 (1), 169–183.
- Schneider, P., 2007. *Provider payment reforms: lessons from Europe and America for South Eastern Europe*. Discussion paper, World Bank, Washington.
- Simar, L., Wilson, P. W., 2000. Statistical inference in nonparametric frontier models: The state of the art. *Journal of Productivity Analysis* 13, 49–78.
- Smith, P. C., 2004. Health care reforms in Europe and their implications for Japan. *The Japanese Journal of Social Security Policy* 3 (2), 80–95.
- Sommersguter-Reichmann, M., 2000. The impact of the Austrian hospital financing reform on hospital productivity: empirical evidence on efficiency and technology changes using a non-parametric input-based malmquist approach. *Health Care Management Science* 3 (4), 309–321.
- Spiegelhalter, D. J., Best, N. G., Carlin, B. P., van der Linde, A., 2002. Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society Series B* 64, 583–640.
- Steinmann, L., Zweifel, P., 2003. On the (in)efficiency of Swiss hospitals. *Applied Economics* 35 (3), 361–370.
- Tsionas, E. G., 2002. Stochastic frontier models with random coefficients. *Journal of Applied Econometrics* 17 (2), 127–147.
- Widmer, P. K., Zweifel, P., Farsi, M., 2010. *Accounting for heterogeneity in the measurement of hospital performance*. Working paper, Socioeconomic Institute.