Ruhr Economic Papers

Annika Frohloff

Cost and Technical Efficiency of German Hospitals

A Stochastic Frontier Analysis

2

Ruhr Graduate School in Economics

Ruhr Economic Papers

Published by

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstraße 150, 44801 Bochum, Germany

Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstraße 12, 45117 Essen, Germany

Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI Essen)
Hohenzollernstrasse 1/3, 45128 Essen, Germany

Ruhr Economic Papers #2

Responsible Editor: Justus Haucap

ISSN 1864-4872 (online) – ISBN 978-3-936454-92-5

Ruhr Economic Papers

#2

Annika Frohloff

Cost and Technical Efficiency of German Hospitals

A Stochastic Frontier Analysis

Ruhr Graduate School in Economics

ECON

Bibliografische Information der Deutschen Nationalbibliothek
Die Deutsche Nationalbibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über http://dnb.d-nb.de abrufbar.

ISSN 1864-4872 (online)
ISBN 978-3-936454-92-5

Annika Frohloff*

Cost and Technical Efficiency of German Hospitals – A Stochastic Frontier Analysis

Abstract
Using a newly available and multifaceted dataset provided by the German Federal Statistical Office, this paper is the first to investigate both technical and cost efficiency of more than 1500 German general hospitals conducting a stochastic frontier analysis. The empirical results for the years from 2000 to 2003 indicate that private and non-profit hospitals are on average less cost and technical efficient than publicly owned hospitals. One explanation for this result may be that German private and non-profit hospitals produce at a longer average length of stay and, thereby, a higher cost per case than public institutions due to the incentives provided by reimbursement schemes until 2004. Furthermore, the paper reveals that non-subsidised hospitals are less efficient than their respective counterparts. Controlling for patients' characteristics (in addition to the constructed case-mix weights), it can be shown that a high ratio of old patients decreases efficiency whereas a high ratio of female patients and a high surgery rate increase it.

JEL Classification: C13, I11, L33

Keywords: Hospital efficiency, ownership, privatisation

March 2007

---

*Ruhr Graduate School in Economics and Ruhr-Universität Bochum. – I am grateful to Thomas Bauer, Jan Brenner, Justus Haucap, Stefanie Schurer, and Andrew Street for useful remarks on earlier drafts of this research. I also thank the employees from the Forschungsdatenzentrum for the nice working atmosphere at the Regional Statistical Office in Düsseldorf. Financial support by the Alfried Krupp von Bohlen und Halbach-Stiftung is gratefully acknowledged. – All correspondence to: Annika Frohloff, Ruhr-Universität Bochum, Department of Economics, Universitätsstr. 150, GC3/60, 44801 Bochum, Germany. Fax: +49 234 32 14311, email: annika.frohloff@rub.de.

1 Introduction

Tight public budgets and increasing per capita expenditures due to technological change, more chronic diseases, and an ageing population characterise today's challenges faced by the German health care system. In 2003, hospital expenditures made up 59.2 billion €, which amounts to 2.7% of the German GDP. Since per capita expenditures for health care have grown by 50% between 1993 and 2003, debates about reforms and inefficiency of the German health system have started in the late nineties and have resulted in several health care reforms.

Moreover, over the last ten years an increasing number of public hospitals have been privatised in Germany. From 1992 to 2003, the share of all public hospitals has decreased from 45% to 36% whereas the share of all private hospitals has increased from 15% to 25%. The share of non-profit hospitals has remained relatively constant over the same period of time.[1]

In Germany, institutions of different ownership types face different tax payments rules. Additional to the exemption of all hospitals from trade tax, property tax, and value added tax on health care related goods, non-profit institutions are released from corporation tax and pay a reduced value added tax rate of 7% for all other goods (§§3-5 UStG and §§51-68 AO). Since non-profit hospitals are by definition not allowed to accumulate profits (except for reinvestments), they have more difficulties than private hospitals to take up credit from the capital market. At the same time, public funding decreases steadily which forces hospitals to invest independently. Public hospitals face similar financial difficulties due to increasing costs and decreasing funding where debts are still publicly compensated in most cases. Furthermore, the organisational structures of non-profit and public hospitals may be less flexible than those of private institutions. Although private hospitals produce at a much longer length of stay than public and non-profit hospitals, their occupancy ratios are lowest. The latter may be due to a possible internal policy that in private hospitals relatively more beds will be provided to guarantee care in any case of demand.

Theoretically, different routes of thought have compared the performance of public vs. private firms (e.g. Agency and Property Rights Theory, Public Choice, and organisation theories).[2] Following different approaches, they all conclude that private firms produce more efficiently than public firms (Villalonga, 2000) in unregulated markets. However, international studies of hospital efficiency (Zuckerman et al., 1994; Rosko, 1999, 2001, 2004; Ozcan et al., 1992) come to the conclusion that private hospitals are less cost efficient than public hospitals.

This research deals with the questions (1) whether there is inefficiency of hospitals and (2) if yes, which exogenous[3] factors like ownership type or patient structure influence estimated inefficiency.[4] The effects of these and other

[1] Following the definition of the German Statistical Office, three hospital types occuring in Germany are distinguished, namely (1) public, (2) non-profit, and (3) private hospitals. Non-profit hospitals are also private, i.e. non-public, but, in contrast to private hospitals, they are run by non-profit organisations such as churches or miners' associations.

[2] Founders and contributors for each route are listed in Villalonga (2000).

[3] With exogenous factors we mean in the following all factors which are neither inputs nor outputs to the production process including both environmental (patient's age) and organisational (nurse to bed ratio) factors.

[4] Inefficiency is defined as the observation's deviation from the estimated or constructed cost or production frontier. Given exogenous input prices and demand driven outputs, the

factors on cost and technical inefficiency will be identified conducting cross sectional stochastic frontier analyses exploiting the newly available German hospital statistics for the period from 2000 to 2003.[5] In order to compare a large number of heterogeneous hospitals, we weight the cases treated in each hospital according to their severity. The weights are constructed exploiting information about patients' diagnoses and lengths of stay. To check the robustness of the signs of the efficiency variables, we estimate their influence on both cost and technical inefficiency and compare the results over the years. For the same reason, different specifications of both models with different samples (trimmed, untrimmed) are estimated.

The rest of the paper is organised as follows. In Section 2, the use of two different methods to measure efficiency (2.1) is discussed and results of existing hospital efficiency studies are presented (2.2). Section 3 is divided into three parts: The estimation strategy is explained in subsection 3.1. The dataset is described in subsection 3.2 before the problem of adjusting cases for severity of illness is discussed in subsection 3.3. The results are presented in section 4. Section 5 concludes.

2 Measuring hospital efficiency: methods and empirical evidence

2.1 Measuring hospital efficiency

The widely used methods to estimate technical or cost efficiency of individual firms can be classified into non-parametric and parametric methods. Non-parametric methods, like Data Envelopment Analysis (DEA) introduced by Charnes et al. (1978), solve an algorithm that constructs the convex hull of the observed data points to define the deterministic cost or production frontier of the hospitals. Parametric methods like Stochastic Frontier Analysis (SFA), simultaneously introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), are based on the idea of estimating a stochastic cost or production frontier, which splits the estimated inefficiency into two components. The first component controls for random noise whereas the second component captures the deterministic inefficiency of the hospital. Maximum Likelihood estimation is used to find a solution to the highly non-linear estimation problem.[6]

This paper applies the SFA-estimation approach for the following reasons. First, SFA allows to control for random unobserved heterogeneity among the firms. The inefficiency effect can be separated from statistical noise. With DEA, any deviation of an observation from the frontier must be attributed to inefficiency, which makes the results very sensitive to outliers or measurement

cost frontier maps minimal costs possible. The *production frontier* maps maximal output feasible given input use (Farrell 1957).

[5]Krankenhausstatistik: Grund- Diagnose- und Kostendaten, 2000-2003, Antrag am Forschungsdatenzentrum der Statistischen Landesämter Nr. 254-2005.

[6]An introductory overview and a survey over both, Data Envelopment Analysis and Stochastic Frontier Analysis can be found in Coelli and et al. (2005) and Lovell (1993). Kumbhakar and Lovell (2000) provide a complete summary of both the theory and techniques used in stochastic frontier production, cost, and profit analysis. Another detailed review is provided by Greene (1997).

error. Especially in an industry which is characterised by a high degree of heterogeneity and uncertainty like the hospital sector, it is important to account for uncontrollable environmental surroundings. Second, by using SFA, the statistical significance of the variables determining efficiency can be verified using statistical tests. Third, the firm specific inefficiency is not measured in relation to the "best" firm, as it is done in non-parametric approaches. Hence, SFA is again less sensitive to outliers in the sample. Disadvantages of the SFA approach consist of the need of distributional assumptions for the two error components as well as the assumption of independence between the error terms and the regressors and about the production technology. Firms' efficiency rankings, which had been estimated using different distributional assumptions, correlate highly (Kumbhakar and Lovell, 2000). However, Street (2003) suggests not to use individual efficiency estimates to set annual performance targets for the hospitals. In this study, mean efficiency estimates are compared between different subgroups where only their relative performance is of interest.

The incorporation of exogenous variables, which are neither inputs nor outputs of the production process but influence the performance of the producer, is crucial for the analysis of hospital efficiency. Examples for this heterogeneity are the ownership type and geographical and demographical aspects. When comparing effects of different exogenous factors using DEA, the non-parametric algorithm is solved separately for each subgroup, which creates potential problems of both small sample bias and a lack of comparability of the estimated efficiency scores between the different groups. The use of the SFA approach developed by Huang and Liu (1994) and generalised for panel data by Battese and Coelli (1995) enables us to estimate and test the significance of the effects of these exogenous variables on mean efficiency in one step. Despite these differences between the two approaches, most authors applying both SFA and DEA find that the resulting efficiency scores are highly correlated.[7]

In general, the estimation of cost efficiency using SFA requires information on input prices, output quantities, and total expenditure on the inputs used. It is assumed that all hospitals seek to minimise costs, which is especially necessary in the case of an underlying Cobb-Douglas production function (Battese and Coelli, 2005; Kumbhakar and Lovell, 2000). In the literature it is still discussed whether this assumption is appropriate to describe the behaviour of non-profit and public hospitals. Although not seeking to maximise profits, non-profit hospitals may e.g. seek to minimise costs for social reasons or for higher wages. When estimating technical efficiency neither any assumption about cost minimising behaviour are imposed nor is it necessary to know input prices; input quantities are sufficient. Although technical efficiency models may be criticised for the need to boil down hospital production to one single output, their lack of assumptions rationalises the estimation of both efficiency models' types.

[7] For a further discussion of advantages and disadvantages of DEA and SFA and for hospitals studies comparing both methods see Jacobs (2001), Chirikos and Sear (2000), Webster et al. (1998), Linna and Häkkinen (1997), and Linna (1998).

2.2 Results of SFA and DEA hospital studies

Empirical evidence on hospital efficiency itself and on the effect of ownership type on their efficiency is scarce.[8] The efficiency of German hospitals has only been investigated with DEA so far. Helmig and Lapsley (2001) use data from 1991 to 1996 aggregated on the three ownership types (public, non-profit and private) and measure the highest inefficiency scores for the group of private hospitals. Over all hospitals, efficiency has increased over time. Staat and Hammerschmidt (2000) focus on 160 hospitals chosen by their comparability with respect to the number and type of departments. They find that the efficiency scores of very similar hospitals differ significantly and that non-profit hospitals are less efficient than other hospitals with respect to the group means. In a more recent application, Staat (2006) applies DEA to two different samples of comparable hospitals in the old federal states of Germany using data from 1994. He calculates mean efficiency scores of .75 for basic care hospitals (108 obs.) and of .89 for basic care hospitals with facilities of regional importance (52 obs.). However, differences between ownership types are not significant. This lack of precision may be attributed to small subsamples. Werblow and Robra (2006) calculate high saving potentials in non-medical departments using aggregated non-medical costs from 2004 differentiated by the three ownership types and 16 federal states (48 observations). Calculated mean efficiency varies much over ownership types and federal states. On average, however, the group of public hospitals is least efficient compared to the other two groups. Steinmann et al. (2003) find that on average in 2002 79% of the Saxonian hospitals are efficient. They do not analyse the effect of ownership.

SFA was applied on hospitals in international studies, though. Although it has been used broadly in other countries to measure *cost* efficiency, it has been to our knowledge applied only twice before to measure *technical* efficiency of hospitals.[9]

In their seminal study, Zuckerman et al. (1994) analyse the effects of ownership type, location and teaching status on cost efficiency of US hospitals by assuming hospital specific variables to shift the cost frontier. When comparing only highly efficient hospitals, private hospitals turn out to be less efficient than non-profit or public hospitals. Zuckerman et al. further detect that male, elderly and surgery rates have a negative effect on the cost frontier.

Using the more recent one-step approach for panel data by Battese and Coelli (1995), which allows to estimate the impacts of the exogenous variables on firm-specific inefficiency directly, Rosko (2001, 2004), Folland and Hofler (2001), and Brown (2003) identify private hospitals to be more inefficient than the other US hospitals.[10] In Switzerland, hospitals do not differ by ownership type (Farsi et al., 2005).

As a low Herfindahl-Hirschman index (HHI) reflects high competition, efficiency should be inverse related to the HHI. Nevertheless, Rosko (1999, 2001, 2004) and Rosko and Chilingerian (1999) find efficiency to be positively related with market concentration. Rosko argues that this result is consistent with the

[8] In his paper about non-parametric and parametric applications measuring efficiency in health care, Hollingsworth (2003) reviews 188 studies published since 1983, of which 73 measure hospital efficiency where 16 use SFA.

[9] Webster et al. (1998), Australia, Folland and Hofler (2001), USA.

[10] Rosko and Chilingerian (1999) and Rosko (1999) come to the same conclusion using the two-step approach introduced by Pitt and Lee (1981).

practice of service-based competition (Rosko, 2001).[11]

With respect to optimal hospital size, findings of stochastic frontier studies differ or contradict each other even within one country, depending on chosen size categories and model design.[12]

3 Estimation strategy and data

Before describing the dataset, the method of cross sectional stochastic frontier analysis incorporating exogenous influences is introduced following Kumbhakar and Lovell (2000).

3.1 Estimation strategy

In this paper, cross sectional stochastic frontier models are estimated for each of the four years under study.[13] To measure cost efficiency for each hospital $i = 1, \ldots, N$, the K input prices $w_i = [w_{1i}, \ldots, w_{Ki}]$ of inputs x_i (three staff groups and medical requirements) are calculated. A stochastic cost frontier with a producer specific random part $\exp(v_i)$ can be written as

$$C_i \geq c(y_i, w_i; \beta) \exp(v_i) \tag{1}$$

where C_i are the observed total adjusted costs of hospital i, y_i is the vector of outputs, and β is the vector of the estimated coefficients. $c(y_i, w_i; \beta)$ represents minimal costs, given outputs y_i and input prices w_i, and defines the part of the cost frontier which is deterministic. The appropriate measure of cost efficiency CE_i is

$$CE_i = \frac{c(y_i, w_i; \beta) \exp(v_i)}{C_i} \leq 1$$

which defines cost efficiency as the ratio of minimum cost feasible in an environment characterised by hospital specific random shocks $\exp(v_i)$ to observed expenditure. For future modelling, we define

$$CE_i =: \exp(-u_i) \tag{2}$$

and assume the inefficiency term u_i to be truncated at zero to assure that efficiency $CE_i \leq 1$.

Since a cost frontier must be linearly homogeneous in input prices, total costs and the other input prices are normalised by dividing them with one fixed input price w_{ki}.[14] Furthermore, as discussed above, it cannot be derived unambiguously from the literature whether there are economies of scale in the hospital

[11] We possess information about the HHI measured in terms of installed beds per county. The literature on antitrust in health care markets suggests to use patient flows instead of geographical aspects to define the relevant market, which is not possible in this study due to data limitations. Therefore, the HHI is not included into the models since the relation between our HHI and competition can be highly questioned.

[12] For US hospitals compare, e.g., Zuckerman et al. (1994) and Ozcan et al. (1992) or for Switzerland, Steinmann and Zweifel (2003) and Farsi and Filippini (2005).

[13] When including one lagged variable in the final model, the sample is reduced to three years.

[14] Here, the price for nursing staff is chosen to normalise the cost frontier. Estimation results do not depend on this choice.

market. Therefore, in both efficiency models we focus on the simple Cobb-Douglas production function -opposed to the more general translog production function- as our main functional form.[15] Assuming that $c(y_i, w_i; \beta)$ takes the log-linear Cobb-Douglas functional form, equation (1) becomes

$$\begin{aligned} \ln \frac{C_i}{w_{ki}} &\geq \beta_0 + \sum_{n \neq k} \beta_n \ln \frac{w_{ni}}{w_{ki}} + \beta_y \ln y_i + v_i \\ &= \beta_0 + \sum_{n \neq k} \beta_n \ln \frac{w_{ni}}{w_{ki}} + \beta_y \ln y_i + v_i + u_i \end{aligned} \tag{3}$$

where v_i is the two-sided random-noise component with mode zero and constant variance and u_i is the nonnegative cost inefficiency component of the composed error $\epsilon_i^c = v_i + u_i$. As in other hospital cost efficiency studies (e.g. Zuckerman et al., 1994; Linna, 1998; Rosko, 2001; Farsi and Filippini, 2005), the weighted number of inpatient cases is chosen as one output y_i.

In the case of technical efficiency, the log-linear *technical* stochastic frontier assuming a Cobb-Douglas production function is defined as

$$\ln y_i = \beta_0 + \sum_n \beta_n \ln x_{ni} + v_i - u_i,$$

i.e. for each hospital i the output y_i is maximised given inputs $x_i = [x_{1i}, \ldots, x_{Ni}]$ and given an environment characterised by random noise v_i and non-negative inefficiency u_i. The derivations for the normal truncated normal production model follow analogously to those for cost efficiency. The log likelihood function and the point estimators for technical efficiency coincide with those of the cost model despite from some sign changes due to the fact that in the case of technical efficiency $\epsilon_i^t = v_i - u_i$ whereas in the case of cost efficiency $\epsilon_i^c = v_i + u_i$.

The nonnegative systematic inefficiency component u_i is in different studies assumed to follow different distributions depending on the question of interest. Leaving studies aside which only analyse estimated efficiency scores, we concentrate on those incorporating exogenous variables into the model. Zuckerman et al. (1994) assume the exogenous variables to shift the cost frontier. In this case u_i follows a half-normal distribution with zero mode and constant variance, i.e. $u \sim N^+(0, \sigma^2)$.

More recent applications of SFA use either the two-step procedure introduced by Pitt and Lee (1981) or the one-step approach introduced by Huang and Liu (1994). The two-step procedure consists of firstly estimating a stochastic frontier assuming a half normal distribution including only input prices and production outputs. Secondly, the exogenous variables are regressed on the expected inefficiency to identify the factors affecting it.[16] The problem is that the distributional assumptions used in either step contradict each other (Coelli et al., 2005), which leads to biased coefficient estimates (Wang and Schmidt, 2002).[17]

[15] Constant returns to scale are also assumed in recent papers by Linna (1998) and Farsi et al. (2005).

[16] Because of the non-linearity of the estimated inefficiency, in the second step e.g. Tobit equations need to be estimated.

[17] In the first step the inefficiency effects are assumed to be independently and identically distributed whereas in the second step the firm-specific characteristics are regressed on the estimated inefficiency.

Here, following the one-step procedure by Huang and Liu (1994),[18] u_i is assumed to be truncated normally distributed and to depend on firm-specific variables $z_i = [z_{1i}, \ldots, z_{Ki}]'$, namely $u_i \sim N^+(z_i\delta, \sigma_u^2)$. That means that u_i is defined by the truncation of the normal distribution at zero with mode $z_i'\delta$ varying over the hospitals and constant variance σ_u^2. The truncated normal distribution provides a more flexible representation of the pattern of efficiency in the data than the half-normal distribution, the latter being a special case of the truncated distribution with $z_i\delta = 0$. In particular, the estimated vector of coefficients δ incorporates the effects of the exogenous variables on the mode of individual inefficiency.

To derive the log likelihood function, it is generally necessary to assume that u_i and v_i are distributed independently of each other and of the regressors. The log likelihood function for both normal-truncated models for a sample of N producers is given by[19]

$$\begin{aligned} \ln L &= \sum_{i=1}^{N} \Big\{ -1/2 \ln(2\pi) - \ln\sigma - \ln\Phi(\mu/\sigma_u) \\ &\quad -\frac{1}{2}\left(\frac{s\epsilon_i^j + \mu}{\sigma}\right)^2 + \ln\Phi\left(\frac{\mu}{\lambda\sigma} - s\frac{\lambda\epsilon_i^j}{\sigma}\right)\Big\} \end{aligned} \tag{4}$$

where $s = -1, j = c$ in the case of cost efficiency and $s = 1, j = t$ in the case of technical efficiency. Therefore, the parameters of the model to be estimated are the vectors of coefficients β and δ, the variance of the composed error $\sigma^2 = \sigma_u^2 + \sigma_v^2$, and the ratio of the standard deviation of the inefficiency component to the standard deviation of the random component $\lambda = \sigma_u/\sigma_v$.

The estimate of producer specific efficiency is derived either by calculating the mean or the mode of the conditional density $f(u_i|\epsilon_i^j) = \frac{f(u_i,\epsilon_i^j)}{f(\epsilon_i^j)}$ or more correctly by estimating the expected value of cost efficiency $CE_i = E[\exp(-u_i)|\epsilon_i^c]$ or technical efficiency $TE_i = E[\exp(-u_i)|\epsilon_i^t]$. These point estimates are inconsistent using cross sectional data because the variation associated with the distribution of $(u_i|\epsilon_i^j)$ is independent of i (Kumbhakar and Lovell, 2000). The inconsistency of the efficiency estimators could be overcome by exploiting the asymptotic properties of the ML-estimator and therefore using a long panel dataset.[20] The parameter estimates from the stochastic frontier estimation, however, are consistent in any case.

Due to Coelli et al. (1999), having assumed a truncated normal distribution for the inefficiency term, the estimated efficiency scores mirror gross efficiency not being fully adjusted for the exogenous influences. Net efficiency values can be obtained by assuming inefficiency to be half-normally distributed and including the exogenous variables into the frontier.[21]

In the following, both technical and cost efficiency are estimated using Stata 8.0. Starting values for the frontier variables are obtained by Ordinary Least

[18] This one-step approach has been generalised for panel data use by Battese and Coelli (1995, 1993)

[19] The derivations for the normal-truncated normal cost model can be received upon request; for the production model compare e.g. Battese and Coelli (1995, 1993).

[20] The derivations for panel data estimators follow analogously (Battese and Coelli, 1995). We do not exploit the panel structure of our data since the definition of the cost variables in the German Hospital Statistics changes from 2001 to 2002 leaving us only two small subpanels.

[21] However, this paper focusses on relative efficiency scores instead of on absolute values.

Squares estimation (OLS), not by a General Method of Moments estimator as it is implemented. This approach turned out to have better convergence properties. Furthermore, the starting values of the coefficients of the exogenous variables are set to zero.

3.2 The dataset

The data used in this study are extracted from the annual hospital statistics, which is collected and administered by the German Federal Statistical Office. This rich dataset contains information on costs, endowments and inpatient stays of all German hospitals.[22]

Our unbalanced sample consists of around 1556 to 1635 general hospitals each year. By restricting the analysis to general hospitals, the eight military hospitals as well as between 350 and 440 specialised clinics like mental institutions or exclusive day- or night hospitals are excluded. Around 200 observations each year are dropped for which the data is inconsistent, e.g. hospitals with costs for doctors or nurses of less than 2€ (410 obs.) or where costs per nurse are higher than costs per doctor (265 obs.). Then, to get the final sample, the dataset is trimmed (dropping another 300 observations in total) by excluding the highest and lowest one percent of the number of weighted cases (leaving hospitals with 127 to 50,348 weighted cases), of beds (leaving hospitals with six to 1,359 beds) and of length of stay (leaving hospitals with 2.5 to 40 days per patient). The sample is trimmed to show that the results, which hold similarly when using the untrimmed dataset, are not outlier driven (weighted cases and beds) and to exclude unreliable data (e.g. mean length of stay of up to 228 days).[23]

To measure *cost* efficiency, total adjusted costs (*total_adj_costs*) are chosen as the dependent variable. For a better comparability of the hospitals, total costs are adjusted by subtracting costs for research and ambulatory care from total hospital costs. The adjusted costs only capture those costs compatible with 'hospital and nursing charges' ("pflegesatzfähige Kosten") which are reimbursed by the health insurance companies. They range from 0.24 to 238 million € per year and hospital, where the mean value over the four years under study is 26.5 million €.[24]

Input prices for the two most important labour variables medical (*price_doc*) and nursing services (*price_nurse*) and for the rest of the staff (*price_other_staff*) are constructed by dividing the costs incurred per group by the respective number of full-time equivalent staff employed within that group. Since a homogeneous cost function is assumed where the sum of the coefficients is one, we need to include all employment groups (Farsi and Filippini, 2005). Analogously, the price for capital (*price_bed*) is calculated by dividing the cost for all medical requirements (which include e.g. pharmaceutical drugs, medical instruments, implants, and transplants) by the number of installed beds. The standard as-

[22] Hospitals are statutory obliged to deliver this information (§17b KHG).

[23] As it will be discussed later, signs and significance levels only depend to a small degree on trimming. The results can e.g. also be gained when dropping the lowest and highest 5% of the two dependent variables weighted cases and total adjusted costs ignoring the huge differences in length of stay.

[24] Using the unadjusted total costs (0.24-359 million €, sample mean: 27.8 million €) yields qualitatively similar results.

sumption of linear homogeneity in input prices is imposed by normalising the cost frontier with respect to the price for nursing services (*price_nurse*).

The *technical* efficiency frontier is constructed analogously to DEA studies of technical hospital efficiency (Ozcan et al., 1992; Helmig and Lapsley, 2001) by choosing the number of weighted cases (*weighted_ cases*) as the dependent variable. The method of weighting is explained in detail in the following subsection. The inputs used are the absolute number of doctors (*docs*), nursing employees (*nurses*) and the other employees (*other_staff*) as well as the number of inpatient days (*days*).[25] Unfortunately, the hospital statistics does not provide information about depreciation rates or other variables which could be used as a proxy for the absolute value of the capital stock.

The exogenous variables are common to both models. To control for observable heterogeneity, the following eight different hospital specific factors are chosen: ownership type, public subsidy status, ratio of nurses to the number of beds, a dummy for being located in the East of Germany, the occupancy rate, and, to capture patients' characteristics, the ratio of female and elderly patients as well as the ratio of surgeries relative to all inpatient stays are used. In this paper, these variables are included in the model to measure their direct effects on inefficiency using the one-step approach discussed in Section 3.1.[26]

In particular, regarding hospital ownership, the performance of private (*private*) and non-profit (*non-profit*) hospitals is compared with the performance of public hospitals forming the base group. We deduce from the international empirical literature the hypothesis that private hospitals are on average less technical and cost efficient than public hospitals. Philipson and Posner (2006) analyse antitrust issues theoretically and find that the same incentives to restrain trade exist in the non-profit sector as in the private (for-profit) sector. In his overview about non-profit ownership and hospital behaviour, Sloan (2000) also concludes that there is no clear empirical evidence for a difference between these two ownership types. Therefore, we postulate that they also turn out to be less efficient than public hospitals. Duggan (2000) uses a change in financing US hospitals to reveal that the difference between the three types is driven by the soft budget constraint of public hospitals. "The decision-makers in private not-for-profit hospitals are just as responsive to financial incentives and are no more altruistic than their counterparts in profit-maximising facilities (Duggan, 2000)."

The third dummy-variable, subsidy status, refers to the question whether a hospital receives public transfers for service provision. Since 1972, German hospital financing is dualistic: the health insurance companies pay for operating costs produced by their insurants while investments are funded by public subsidies for which hospitals need to apply and which are negotiated yearly. The subsidies often consist of a fixed payment intended for infrastructural rein-

[25] Maximising the number of cases when including the number of days as input could be interpreted as minimising the hospital's simple length of stay which may be defined as the sum of days divided by the number of all weighted cases. It does not coincide exactly with the average length of stay of the hospital reported in table 1, which is measured in terms of the lengths of stay of single diagnoses.

[26] Smith and Street (2004) argue that it depends on the question and market under study whether to include all exogenous variables. They suggest to exclude those factors from the model which may be influenced by the producers (e.g. subsidy status) and only compare mean efficiency scores of subgroups (e.g. non- vs. subsidised hospitals) after estimation. However, statistical testing of the significance of the excluded factors' influence is then difficult.

vestments and a variable part paid per bed. One third of the private general hospitals does (also voluntarily) not receive these subsidies whereas only two percent of all general non-profit and public hospitals is not publicly subsidised. The eventually paid rates depend much on the federal state's financial situation and on the bargaining strength and effort of the single hospitals.

The dummy-variable (*no_subs*) is replaced by its first lag (no_subs_{-1}) arguing that subsidies, especially investments for the hospital's infrastructure, do only have an intermediate effect on inefficiency instead of affecting it in the same year. Moreover, private hospitals form the majority (76-80%) in the group of the 91 to 109 non-subsidised hospitals while representing the minority (15%) of all hospitals in the sample. To capture only the pure effect of the subsidy status, the lagged dummy-variable is interacted with each of the three ownership types (e.g. $(no\_subs \times private)_{-1}$).[27] We also estimate the model without this variable and then compare expected mean efficiency values for each subsidy status.

Analogously to the results by Farsi and Filippini (2005) and to theoretical considerations about firm efficiency, it is postulated that the higher the nurse per bed ratio (*nurse/bed*) the higher the inefficiency. Regarding the regional dummy (*east*), hospitals located in the 'new' federal states (including Berlin) have on the one hand profited by the public investments after reunification. On the other hand, in Germany, higher unemployment rates in the East induce migration of mainly young and skilled inhabitants from the East to the West. The only German DEA study comprising regional characteristics notes mixed results with respect to efficiency values and saving potentials over Eastern and Western federal states with five Eastern federal states being in the group of the six most technical efficient and Berlin's hospitals being the least efficient in Germany (Werblow and Robra, 2006). Finally, a higher occupancy rate (*occupancy_rate*) should be mirrored by lower inefficiency.

The patients' dataset provides us with information about 17 million individual patients treated each year (gender, age, length of stay, main diagnosis, death status) aggregated on hospital specific main diagnoses (ICD-10 Version 2.0 (International Classification of Diseases and Related Health Problems), three digits) summing up to 830,000 and 923,000 observations each year. In addition to our case-mix weights, which will be defined in subsection 3.3, and analogously to Zuckerman et al. (1994), the ratio of female patients (*female_rat*), of more than 75 years old (*plus75_rat*), and of surgeries per case (*surgery_rat*) are used as further exogenous variables. Whereas a high ratio of elderly patients should increase inefficiency values e.g. because of adverse side-effects and multi-morbidity, a high surgery rate should decrease them because of 'learning-by-doing' effects. A high ratio of female patients could involve higher efficiency because in gynaecological departments treatments and surgeries are highly standardised.[28]

[table 1 about here]

Table 1 reports descriptive statistics of the final sample. The table shows average numbers over the four years under study for all hospitals in the sample

[27] If we excluded all non-subsidised hospitals from the sample we would exclude one third of the private hospitals. Nevertheless, results hold similarly.

[28] In the original paper by Zuckerman et al. (1994) a high ratio of elderly patients, male patients and surgeries have a negative effect on the cost frontier.

as well as for each ownership type separately. The high variances reveal that the hospitals under study are highly heterogeneous with respect to almost all variables considered.

In the last part of Table 1, numbers are presented, which are not included in the model specification but which yield further insights regarding the different ownership types. On the one hand, costs *per bed* are lower in almost every cost category for private and non-profit hospitals compared to public hospitals. E.g. adjusted total costs per bed are 2.6% (5.5%) lower in private (non-profit) hospitals than in public institutions. On the other hand, costs *per case* are 15% (1%) higher in private (non-profit) institutions than in public hospitals. In our sample of general hospitals of the period from 2000 to 2003, average length of stay turns out to be 2.5 days higher in private than in public institutions, which may be partly attributed to the system of cost reimbursement. While these differences decline over time, hospitals' occupancy rates defined as $occ\_rate = days/(beds \cdot 365)$ are always highest in the group of public hospitals.

Other interesting facts are that, on the one hand, private hospitals face the highest ratio of beds hired out to external physicians ("Belegbetten"), which is supposed to increase occupancy rates and thus efficiency. On the other hand, only 59% of the private hospitals provide ambulatory care, which would avoid more expensive inpatient stays, whereas 94% of the public and 89% of non-profit hospitals offer such a service.[29] On average, 2.5% of the patients die in the hospital.

Although providing detailed information on almost all aspects, the dataset does neither include quality measures[30] nor information about patients' health insurance types. Different efficiency studies including quality measures reveal that quality has little impact on estimated outcomes (Zuckerman et al., 1994; Vitaliano and Toren, 1996). Sloan et al. (2001) show that US hospitals do not differ with respect to quality outcomes in terms of survival rates, changes in functional and cognitive status, and living arrangements. "So while the use of a valid measure of quality would be desirable, a priori assumptions about the impact of the exclusion of quality measures (which are difficult to obtain) cannot be made" (Rosko, 2001). Thus, we assume that minimal quality requirements are fulfilled by all hospitals and that they do not differ systematically with respect to e.g. ownership type. In our study, having higher costs or treating less cases due to extraordinary high quality will be reflected by higher inefficiency.

In Germany, only around 10% of the population are privately insured. Nevertheless, higher ratios of privately insured patients relative to all patients may lead to higher costs per case through the provision of more (costly) treatments. In this paper, privately or public ('gesetzlich') insured patients are assumed to be equally distributed across all ownership types for two reasons. Firstly, for general hospitals, demand is mainly determined by geographical and demographical surroundings. Secondly, in the Eastern part of Germany, the ratio of privately insured inhabitants is far lower than in the West due to differences in income and employment rates. At the same time, speaking against the hypothesis that public insured patients are underrepresented in private hospitals, a high

[29] In the cost model, total adjusted costs are adjusted for costs for ambulatory care and research expenses, while the production model is not adjusted.

[30] The death ratio is not used as a quality indicator. It is impossible to distinguish between the influence of the hospital and the patient's health status, especially since the statistic does neither provide information about return ratios nor about post-mortality rates.

ratio of private hospitals (24% compared to 19% (13%) of all public (non-profit) hospitals) can be observed in Eastern Germany.

3.3 Constructing case-mix weights

Hospitals differ with respect to the severities of illnesses their patients suffer from due to demographic or geographic surroundings or specialisation. Therefore, they face different costs and burdens. If, e.g. due to demographic reasons, one hospital serves more severe and hence more costly cases than another, anything else equal it would turn out to be less efficient. Theoretically, when estimating a multiple output cost frontier, each single diagnosis treated could be included as a different output. This approach is not feasible because of data and estimation restrictions.

Hence, most authors add a scalar measure of patient mix such as the Medicare Case-Mix Index (MCI) for U.S. hospitals (Ozcan et al., 1992; Rosko, 1999, 2001, 2004) to their model.[31] Mirroring resource use based on cost information, there is nevertheless one problems inherent to this index. Medicare patients do neither cover all emerging diagnoses nor all treatments so that the index might be biased. However, Rosko and Chilingerian (1999) demonstrate for U.S. hospitals that the inclusion of an inter-DRG case-mix index reduces inefficiency measures by 50%.

Similar indices exist in Europe which are used by Linna and Häkkinen (1997) and Linna (1998) studying Finnish hospitals, and Jacobs (2001) in a study of UK hospitals.

Different to those studies, in this paper severity-of-illness weights are extracted by exploiting the information about the average length of stay of each inpatient diagnosis in Germany, where each stay is counted at least as a one-day stay. Using the 830,000 to 923,000 observations per year, a mean length of stay (los) for each year[32] for each of the up to 1,730 main diagnoses $m = 1, \ldots, M$ over all 2,290 German hospitals $i = 1, \ldots, N$ is calculated: $los_m = \frac{1}{N} \sum_i^N (days_{mi}/cases_{mi})$.

The mean length of stay over all diagnoses and all hospitals in the full dataset is $los_G = \frac{1}{M} \sum_m los_m$, which e.g. amounts to 8.9 days in 2003. Finally, the number of weighted cases of a single hospital i is defined as

$$weighted\_cases_i = \sum_m^M \frac{los_m}{los_G} cases_{mi} = \sum_m \pi_m cases_{mi}$$

with $\frac{1}{M} \sum_m^M \pi_m = 1$. The weight π_m is bigger (smaller) than one if the treatment of diagnosis m takes more (less) time than the overall German average. These weights serve as an alternative to the usual cost-based case-mix weights

[31] The MCI is the distribution of a hospital's Medicare patients across more than 470 diagnosis related groups (DRGs) weighted by the relative average charge of treating the typical U.S. Medicare patient in the DRG. German hospitals are using ICD-10 Version 2.0 (International Classification of Diseases and Related Health Problems) for Diagnosis-Coding and OPS-301 for Procedure-Coding (OPS are any kind of operations or treatments needed to specify a diagnosis). As in other countries combining the up to 50 ICDs and up to 100 OPS of one treated patient a computer algorithm (so called grouper) determines one corresponding DRG for the particular case which corresponds to a fixed price.

[32] For ease of illustration, the time index t is suppressed.

relying on the idea that length of stay proxies resource use of different diagnoses well. The advantages of these weights compared to the CMI are that they are constructed from all annual inpatient diagnoses occurring in Germany, which overcomes potential selection bias. Furthermore, information requirements are easier to fulfil than if a cost-based index would be used. This method is fully transparent and easily re-calculable. Comparing the variable *cases* with *weighted_cases*, in our sample between $-7,065$ and $6,250$ cases or between -60% and 140% of the cases are added due to weighting. The unweighted sum of weights of each hospital $\sum_{mi}^{M_i} \pi_{mi}$ ranges between 0.55 and 2.18.[33]

4 Results

In this paper a cross sectional normal-truncated normal model of technical efficiency and of cost efficiency is estimated for each year between 2001[34] and 2003.[35] The underlying assumptions discussed in chapter 3.1 can be summarised as follows: For both models it is assumed that a Cobb-Douglas production function represents the technology available to all hospitals and that inefficiency follows a truncated-normal distribution. Additionally, the cost model exhibits a homogeneous cost function and cost minimising behaviour by all hospitals. Estimation results hold with respect to the above stated assumptions and are reported in Table 2 (technical efficiency) and Table 3 (cost efficiency). The hypothesis of inefficiency u_i to be half-normally distributed and to be independent of the exogenous variables can be rejected for each year under study independent of whether we include the exogenous variables into the model, i.e. the mode of the corresponding distribution function varies over the hospitals. Over the three years, the sign of almost all coefficient estimates coincide with each other in both models. Although standard errors and the coefficient values may differ between the years and the models, in general both tables show similar results.

[tables 2 and 3 around here]

The estimated coefficients for the effect of input prices on the cost frontier and of the inputs on the technical frontier are presented in the first part of the table. They are very similar within the models across the years and highly significantly different from zero (except of the number of caring staff in the technical frontier in 2002). They also show the expected positive effects on the respective dependent variables.[36]

The coefficient estimates of the exogenous factors in the second part of the table are read as effects on *in*efficiency. First and most importantly, they reveal that both private and non-profit ownership have a positive effect on inefficiency in Germany. Despite the fact that our results for the years 2001 to 2003 confirm international studies, we interpret them cautiously with regard to policy

[33] When estimating the models without controlling for severity of illness, all signs of the estimated coefficients coincide with our final estimates (where significant). Standard errors decrease.

[34] The first year is dropped due to the lagged variable no_subs_{-1} included into the model. If we do not use lagged variables, the results hold similarly for 2000, too.

[35] For an explanation why the panel structure of our dataset is not exploited see footnote 20.

[36] Using unadjusted total costs instead of adjusted costs influences the results only slightly, namely such that non-profit ownership and Eastern Germany are not significantly different from zero any more in 2002 and 2003.

implications. Privatisation of public and non-profit hospitals has started in the late nineties and has not for a long time yet finished. Structural and managerial changes may need more time to precipitate efficiency improvements. Public authorities mainly privatised their hospitals in order to rehabilitate their finances and to dispose of the hospitals in deficit. Furthermore, as it is well-known from studies analysing profits and debts of German hospitals, public hospitals front a much higher risk of insolvency and closure (Augurzky et al., 2004). It is possible that, given the incentives provided by the system of cost reimbursement, private hospitals may gain profits accepting simultaneously that they do not produce on a technical or cost efficient scale.[37]

One solution to this seeming contradiction lies in the regulatory regime. The former system of cost reimbursement induces profit maximising hospitals to increase occupancy rates by increasing the lengths of stay. Although producing more costly, they may still gain profits given the prevailing price regime. The introduction of capitation fees in 2004 and a probable subsequent decrease of the average lengths of stay may reduce the differences between the ownership types. This question will be left to our further research.

The result that private hospitals are less efficient than public hospitals does not imply that hospitals which have been privatised are less or more efficient than if they had not been privatised. To answer the question whether privatisation per se yields to a higher efficiency, a difference-in-difference approach would have to be applied on the group of ownership-changers where the privatised hospitals (treatment group) could be compared to a non-privatised (i.e. non-treated) group of public or non-profit hospitals before and after the treatment. However, only 0.8% of the general hospitals have been privatised between 2000 and 2003.

Hospitals which had not received subsidies the year before are significantly more inefficient than those having been partly or fully subsidised, independent of ownership type.[38] Yearly negotiations about the amount of public funding and the need to justify its spending may yield hospitals to produce more efficiently. To understand the effect of the subsidies on hospital efficiency better, it would again be desirable to apply the difference-in-difference estimator discussed above which is again not possible due to the small group of hospitals changing their subsidy-state.

Table 2 reveals that technical inefficiency remains unaffected by occupancy-rates and location. Looking at the cost model (table 3), however, having higher capacity utilisation and being located in the West are associated with lower cost inefficiency. The former finding could be explained by the fact that technical efficiency does not include the costs of empty beds or any other variable capturing capital use. The latter could reveal regional price differentials. Hospitals employing more nurses per bed are more inefficient in both models, which validates theoretical considerations about firm efficiency.

Looking at the patient characteristics, higher female- and surgery ratios incorporate significantly lower inefficiency. This reduction could be due to more standardised treatments in gynaecological departments and learning-by-doing, respectively. Dealing with multi-morbidity and higher risk of adverse side-

[37]It would be interesting to estimate profit efficiency but the dataset does not provide information about profits or revenues.

[38]If the hospitals which do not receive subsidies are dropped, relative results remain mainly unaffected.

effects, the ratio of more than 75-years old patients affects efficiency negatively.

In a last step, the stochastic frontier estimation results are used to estimate expected efficiency scores $E[\exp(-u_i)|\epsilon_i]$.[39] Over the years 2001 to 2003, average estimated mean technical (cost) efficiency is measured to be around 87% (83%).[40] Although efficiency scores range between 25% (12%) and 99% (98%), they are clustered around their mean value due to the underlying normal truncated normal distributional assumption. Since both models yield the same results with respect to the sign of the coefficients as well as similar efficiency estimates, our results are robust with respect to the model used. This observation is confirmed by ranking the hospitals with respect to their estimated efficiency scores. The two rankings (cost and technical efficiency) correlate highly for each of the three years with a correlation coefficient of at least 0.7.

Descriptive statistics reveal that average estimated efficiency scores differ much between the different ownership types. Whereas the public hospitals are in the final model on average around 90.5% technically efficient and $85\%-86\%$ cost efficient, private hospitals manage to increase their efficiency scores from 77% to 82% and from 71% to 76%, respectively, still being at the lowest level. Taking up a middle position, efficiency scores of non-profit hospitals stay relatively constant over time ($86\% - 87\%$ technical efficient and $82\% - 84\%$ cost efficient).

For further robustness checks, the models were estimated using different samples and frontier variables (results are not reported). First, estimating for each year under study the half-normal model including the exogenous variables into the frontier specification (analogously to Zuckerman et al. (1994)) as well as simple OLS, the direction of the effects of the exogenous variables on costs and the number of cases can be confirmed (with a single exception: non-profit ownership is not significantly different from zero in the half-normal case in 2002). Second, if the weighted number of cases is replaced by the unweighted number of cases, the signs of the coefficient estimates and their relative values coincide with the results obtained by using the final sample. Estimated standard errors and efficiency scores, however, decrease.

Third, if the sample is not trimmed, i.e., contrary to our final sample the smallest and biggest general hospitals are included (adding around 60 hospitals per year), the signs of the estimated coefficients and their significance levels persist over the time and coincide with our presented results in both models with one exception.[41] In the cost model, the only difference is that non-profit ownership is not significantly different from zero in 2002.

Fourth, if the specification of the truncated-normal model is changed such that it is not controlled for ownership type and subsidy status conducting the one-step estimation method, some of the remaining exogenous variables do not have a significant impact for some years and efficiency estimates increase. However, if then mean estimated efficiency scores of the subgroups are compared, we again find, that public hospitals have on average the highest scores whereas private hospitals have the lowest both on a higher level than in the final speci-

[39] As explained in subsection 3.1, these estimates are inconsistent not using very long panel data.

[40] These values are presented for illustrative reasons, depend on model specification and increase with the inclusion of exogenous variables or the exclusion of the ownership dummies.

[41] In the technical model, the occupancy rate has a negative impact on inefficiency in 2001 when using untrimmed data while it is weakly significantly positive in 2003 when using the final sample.

fication.[42]

These robustness checks show that, additional to the consistency of the estimated results across the two models, both models are very robust with respect to sample selection and specification.

5 Conclusion

This study is the first to analyse the efficiency of German general hospitals accounting for the heterogeneity in their organisations' and patients' characteristics conducting a stochastic frontier analysis. In addition, this paper is the first to construct case-mix weights based on average lengths of stay including all inpatient stays of all health insurance types.

Using the one-step approach developed by Huang and Liu (1994), and assuming a constant returns to scale production technology, the results of international studies with respect to most of the exogenous influences on hospital efficiency can be confirmed for Germany. First and most important, it is shown that private and non-profit ownership are associated with both higher cost inefficiency and higher technical inefficiency compared to public ownership in each of the years from 2001 to 2003. If the incentives provided by the regulatory regime are such that it is profitable to keep patients, at least at the margin, longer than medically required,[43] privatisation does not need to increase technical or cost efficiency. In fact, this study reveals that privatisation needs to be complemented by an appropriate regulatory framework. However, the fact that private hospitals are less technical and cost efficient than public hospitals should not be confounded with the fact that privatisation of an inefficient public hospital may reduce inefficiency compared to the counter-factual situation in which the particular hospital had not been privatised. This question is left for further research.

Over all ownership type, hospitals which had not been incorporated in the federal hospital planning one year before, turn out to be on average more inefficient than those having been partly or fully subsidised. Hospitals with a relatively high number of nursing staff per bed are aligned with higher inefficiency in both models, where the location in the West and a high occupancy-rate only influence *cost* inefficiency negatively. Regarding the hospital specific patient characteristics, the results indicate that a high ratio of more than 75-years old patients has a positive effect on both cost and technical inefficiency, whereas a high surgery ratio and a high ratio of female patients affect it negatively. Estimated individual mean efficiency varies much over the hospitals due to their heterogeneity. Nevertheless, the majority of the hospitals is clustered around the expected mean efficiency scores of 87% (technical efficiency) and 83% (cost efficiency). Since estimated average cost and technical efficiency scores are very similar and the hospital rankings of both efficiency models correlate highly, the results are considered as robust with respect to the frontier model.

In this first attempt to analyse the efficiency of German hospitals, the technology is restricted to have constant returns to scale, which could be overcome by assuming a translog functional form. For this reason and for the application

[42] The same holds for a simple comparison of non-subsidised and subsidised hospitals.

[43] Until 2004, hospitals faced a system of cost reimbursement.

of advanced panel data methods, the use of long panel datasets would be desirable. For instance the so called "true" fixed effects approach introduced by Greene (2005) would enable us to additionally capture *unobserved* heterogeneity of the hospitals. A further improvement would be to complement the German hospital statistics with information about patients' health insurance types or hospital quality. In future research it would be of interest to evaluate the introduction of capitation fees in 2004 and the subsequent changes in length of stay and estimated efficiency of private, non-profit and public German hospitals.

References

[1] Aigner D, Lovell K, Schmidt P. Formulation and estimation of Stochastic Frontier Production Function Models. *J Econometrics* 1977; **6**:21–37.

[2] Augurzky B, Engel D, Krolop S, Schmidt CM, Terkatz S. Insolvenzrisiken von Krankenhäusern - Bewertung und Transparenz unter Basel II. Materialien 15, Rheinisch Westfälisches Institut für Wirtschaftsforschung, 2004.

[3] Battese GE, Coelli T. A stochastic frontier production function incorporating a model for technical inefficiency effects. Working Papers in Econometrics and Applied Statistics 69, University of New England, 1993.

[4] Battese GE, Coelli T. A model for technical inefficiency effects in a stochastic frontier production model for panel data. *Empir Econ* 1995; **20**:325–332.

[5] Brown S III. Ownership and inefficiency. *Health Econ* 2003; **12**(2):149–158.

[6] Charnes A, Cooper W, Rhodes E. Measuring the efficiency of decision making units. *Eur J Oper Res* 1978; **2**(6): 429–444.

[7] Chirikos TN, Sear AM. Measuring hospital efficiency: A comparison of two approaches. *Health Serv Res* 2000; **34**(6):1389–1408.

[8] Coelli T, Perelman S, Romano E. Accounting for environmental influences in stochastic frontier models: With application to international airlines. *J Productivity Analysis* 1999; **11**(3): 251–273.

[9] Coelli T, Prasada Rao DS, Battese GE. *An Introduction to Efficiency and Productivity Analysis,* 2^{nd} *edition*. Kluwer Academic Publishers: Norwell, Dordrecht, 2005.

[10] Duggan MG. Hospital ownership and public medical spending. NBER WP No. W7789, 2000.

[11] Farrell MJ. The Measurement of Productive Efficiency. *J R Stat Soc ser A* 1957; **120**:253–281.

[12] Farsi M, Filippini M. An analysis of efficiency and productivity in Swiss hospitals. Working Paper 05/01, Quaderno, 2005.

[13] Folland ST, Hofler RA. How reliable are hospital efficiency estimates? Exploiting the dual to homothetic production. *Health Econ* 2001; **10**:683–698.

[14] Greene WH. Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *J Econometrics* 2005; **126**:269–303.

[15] Greene WH. Frontier production functions. In *Handbook of Applied Econometrics, Vol. II*, Pesaran MH, Schmidt P (eds). Blackwell Publishers: Oxford, 1997; 81–166.

[16] Helmig B, Lapsley I. On the efficiency of public, welfare and private hospitals in Germany over time - a sectoral DEA-study. *Health Serv Manage Res* 2001; **14**:263–274.

[17] Hollingsworth B. Non-parametric and parametric applications measuring efficiency in health care. *Health Care Manage Sci* 2003; **6**(4):203–218.

[18] Huang CJ, Liu J-T. Estimation of a non-neutral stochastic frontier production function. *J Prod Ana* 1994; **5**:171–180.

[19] Jacobs R. Alternative methods to examine hospital efficiency: Data Envelopment Analysis and Stochastic Frontier Analysis. *Health Care Manag Sci* 2001; **4**:103–115.

[20] Kumbhakar SC, Lovell K. *Stochastic Frontier Analysis.* Cambridge University Press: Cambridge, 2000.

[21] Linna M. Measuring hospital cost efficiency with panel data models. *Health Econ* 1998; **7**:415–427.

[22] Linna M, Häkkinen U. Determinants of cost efficiency of Finnish hospitals: A comparison of DEA and SFA. Working paper, National Research and Development Centre for Welfare and Health, Finland, 1997.

[23] Lovell CAK. Production frontiers and productive efficiency. In *The Measurement of Productive Efficiency: Techniques and Applications*, Fried HO, Lovell CAK, Schmidt SS (eds). Oxford University Press: New York, 1993; 3–67.

[24] Meeusen W, van den Broeck J. Efficiency estimation from Cobb-Douglas production functions with composed error. *Int Econ Review* 1977; **18**(2):435–444.

[25] Ozcan YA, Luke RD, Haksever C. Ownership and organizational performance: A comparison of technical efficiency across hospital types. *Med Care* 1992; **30**(9):781–794.

[26] Philipson TJ, Posner RA. Antitrust in the not-for-profit sector. NBER Working Paper No. W12132, 2006.

[27] Pitt MM, Lee L-F. The measurement and sources of technical inefficiency in the Indonesian weaving industry. *J Dev Econ* 1981; **9**:43–64.

[28] Rosko MD. Impact of internal and external environmental pressures on hospital inefficiency. *Health Care Manag Sci* 1999; **2**:63–74.

[29] Rosko MD. Cost efficiency of US hospitals: A stochastic frontier approach. *Health Econ* 2001; **10**:539–551.

[30] Rosko MD. Performance of U.S. teaching hospitals: A panel analysis of cost inefficiency. *Health Care Manag Sci* 2004; **7**:7–16.

[31] Rosko MD, Chilingerian JA. Estimating hospital inefficiency: Does case mix matter? *J Med Sys* 1999; **23**(1):57–71.

[32] Sloan FA, Picone G, Taylor D, Chou SY. Hospital ownership and cost and quality of care: Is there a dime's worth difference?. *J Health Econ* 2001; **20**(1):1–21.

[33] Sloan FA. Not-for-profit ownership and hospital behavior, In *Handbook of Health Economics, 1B*, Culyer AJ, Newhouse JP (eds). Elsevier: Amsterdam, 2000; 1141–1174.

[34] Smith P, Street A. Measuring the efficiency of public services: the limits of analysis. *Unpublished Working Paper*, Centre for Health Economics 2004.

[35] Staat M, Hammerschmidt M. Benchmarking the health sector in Germany - an application of Data Envelopment Analysis. Research paper, Institute for Market-Oriented Management, University Mannheim, 2000.

[36] Staat M. Efficiency of hospitals in Germany: A DEA-bootstrap approach. *Appl Econ* 2006; **38**:2255–2263.

[37] Statistisches Bundesamt. Krankenhausstatistik: Grund- Diagnose- und Kostendaten, 2000-2003. Antrag am Forschungsdatenzentrum der Statistischen Landesämter Nr. 254-2005, 2005.

[38] Steinmann L, Dittrich G, Karmann A, Zweifel P. Measuring and comparing the (in)efficiency of German and Swiss hospitals. Working Paper, 2003.

[39] Street A. How much confidence should we place in efficiency estimates? *Health Econ* 2003; **12**: 895-907.

[40] Villalonga B. Privatization and efficiency: Differentiating ownership effects from political, organizational, and dynamic effects. *J Econ Behav Organ* 2000; **42**:43-74.

[41] Vitaliano D, Toren M. Hospital cost and efficiency in a regime of stringent regulation. *East Econ J* 1996; **22**:161-184.

[42] Wang H-J, Schmidt P. One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *J Productivity Analysis* 2002; **18**:129–144.

[43] Webster R, Kennedy S, Johnson L. Comparing techniques for measuring efficiency and productivity of Australian private hospitals. Working Paper 1351.0, ABS Catalogue, 1998.

[44] Werblow A, Robra B-P. Einsparpotenziale im medizinfernen Bereich deutscher Krankenhäuser eine regionale Effizienzfront-Analyse. In *Krankenhausreport 2006- Schwerpunkt: Krankenhausmarkt im Umbruch*, Klauber J, Robra B-P, Schellschmidt H (eds). Schattauer: Stuttgart, 2006; 133–151.

[45] Zuckerman S, Hadley J, Iezzoni L. Measuring hospital efficiency with frontier cost functions. *J Health Econ* 1994; **13**(3):255–280.

6 Appendix

	Total		**Public**		**Non-profit**		**Private**	
variable	**mean**	**s.d.**	**mean**	**s.d.**	**mean**	**s.d.**	**mean**	**s.d.**
output/costs								
cases [in 1,000]	9.01	7.76	11.46	9.29	8.38	5.83	4.39	5.41
weighted_cases [in 1,000]	8.90	7.60	11.28	9.17	8.25	5.61	4.49	5.40
total_adj_costs [in mio €]	26.50	28.10	34.70	36.60	23.50	18.00	13.40	17.60
inputs								
days [in 1,000]	80.12	66.49	100.41	81.27	74.84	47.60	41.94	47.67
docs[a]	53.66	70.96	73.11	97.47	45.34	38.49	25.50	37.89
nurses[a]	158.99	154.92	208.07	199.41	142.63	99.71	76.89	96.03
price_doc[b] [in 1,000€]	84.59	18.58	85.15	12.05	84.95	18.66	82.00	29.55
price_nurse[b] [in 1,000€]	42.88	6.33	44.08	5.11	43.31	54.20	38.47	9.18
price_bed [in 1,000€]	14.21	12.55	14.30	9.39	13.30	10.12	16.56	22.18
exogenous variables								
no_subs	0.06	0.24	0.02	0.13	0.02	0.12	0.31	0.46
occupancy_rate	0.78	0.10	0.79	0.08	0.78	0.09	0.75	0.18
nurse/bed	0.54	0.16	0.56	0.12	0.54	0.15	0.50	0.26
east	0.17	0.38	0.19	0.39	0.13	0.34	0.24	0.42
female_rat	.56	.09	0.55	0.07	0.57	0.09	0.56	0.15
75plus_rat	.21	.11	0.21	0.08	0.22	0.13	0.16	0.13
surgery_rat	.43	.27	0.43	0.23	0.42	0.25	0.43	0.37
other figures of interest								
av. length of stay per hosp.	10.06	4.24	9.22	2.87	10.26	4.02	11.67	6.68
beds	276.42	218.74	342.62	265.31	261.65	159.63	144.69	153.47
total costs/case	3,014	1,230	2,951	952	2,968	1,013	3,311	2,105
total_adj_costs/case	2,909	1,174	2,820	805	2,880	995	3,232	2,076
total costs/bed [in 1000€]	91.13	35.47	94.70	31.31	88.18	27.85	90.24	57.71
total_adj_costs/bed [in 1000€]	87.86	33.30	90.42	26.50	85.45	26.79	88.10	57.30
Sample size N	6,461		2,610		2,860		991	

Table 1: Descriptive Statistics of the sample of the Hospital Statistics, Federal Statistical Office, Germany. Average over the years 2000-2003. a: number of full time equivalent employees, b: costs per full time equivalent employee.

Table 2: Technical efficiency of German hospitals, 2000-2003. Standard errors in parentheses. Significance level: *** $p < .01$, ** $p < .05$, * $p < .1$

ln weighted_cases	2001	2002	2003
		Frontier estimates	
ln docs	0.164 (0.015)***	0.178 (0.014)***	0.139 (0.013)***
ln care	0.079 (0.023)***	0.037 (0.023)	0.079 (0.023)***
ln other_staff	0.086 (0.018)***	0.037 (0.016)**	0.071 (0.016)***
ln days	0.589 (0.021)***	0.666 (0.021)***	0.630 (0.021)***
constant	1.086 (0.148)***	0.646 (0.146)***	0.833 (0.142)***
		effects on μ	
private	1.610 (0.404)***	0.974 (0.257)***	1.319 (0.453)***
non-profit	1.039 (0.303)***	0.615 (0.188)***	0.974 (0.354)***
$(\text{no\_subs}\times\text{private})_{-1}$	0.768 (0.221)***	1.023 (0.224)***	1.379 (0.410)***
$(\text{no\_subs}\times\text{non-profit})_{-1}$	1.508 (0.383)***	1.631 (0.354)***	1.915 (0.538)***
$(\text{no\_subs}\times\text{public})_{-1}$	2.627 (0.643)***	1.817 (0.432)***	2.182 (0.731)***
east	0.182 (0.154)	0.006 (0.130)	-0.166 (0.187)
nurse/bed	0.780 (0.250)***	0.380 (0.264)	0.813 (0.400)**
occupancy_ratio	-0.033 (0.487)	0.091 (0.360)	0.911 (0.519)*
plus75_ratio	0.789 (0.387)**	1.689 (0.389)***	2.327 (0.711)***
surgery_ratio	-2.930 (0.686)***	-1.640 (0.364)***	-1.900 (0.596)***
female_ratio	-1.069 (0.551)*	-1.437 (0.432)***	-1.710 (0.720)**
constant	-1.580 (0.684)**	-1.003 (0.506)**	-2.728 (1.075)**
σ_u^2	0.304	0.210	0.303
σ_v^2	0.011	0.009	0.010
$\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$	0.966	0.957	0.970
Log likelihood	605.286	693.056	692.309
N	1556	1549	1565

Table 3: Cost efficiency of German hospitals, price for nursing staff used for normalisation, 2000-2003. Standard errors in parentheses. Significance level: *** $p < .01$, ** $p < .05$, * $p < .1$

ln total_adj_costs	2001	2002	2003
		Frontier estimates	
ln price_doc	0.105	0.149	0.110
	(0.033)***	(0.033)***	(0.035)***
ln price_otherstaff	0.219	0.180	0.226
	(0.029)***	(0.030)***	(0.030)***
ln price_bed	0.186	0.255	0.215
	(0.016)***	(0.015)***	(0.015)***
ln weighted_cases	1.020	0.987	0.999
	(0.009)***	(0.009)***	(0.009)***
constant	-3.027	-2.668	-2.834
	(0.097)***	(0.095)***	(0.100)***
		effects on μ	
private	0.802	0.834	0.766
	(0.185)***	(0.247)***	(0.214)***
non-profit	0.361	0.288	0.353
	(0.125)***	(0.162)*	(0.144)**
(no_subs×private)$_{-1}$	0.942	1.263	1.232
	(0.182)***	(0.272)***	(0.258)***
(no_subs×non-profit)$_{-1}$	1.665	2.249	1.843
	(0.319)***	(0.480)***	(0.409)***
(no_subs×public)$_{-1}$	1.879	2.053	1.804
	(0.380)***	(0.507)***	(0.447)***
east	0.370	0.414	0.228
	(0.116)***	(0.168)**	(0.133)*
nurse/bed	1.702	2.073	1.986
	(0.231)***	(0.370)***	(0.338)***
occupancy_ratio	-2.570	-3.026	-1.982
	(0.478)***	(0.611)***	(0.458)***
plus75_ratio	0.380	1.438	1.031
	(0.319)	(0.429)***	(0.378)***
surgery_ratio	-1.390	-1.762	-1.119
	(0.257)***	(0.387)***	(0.289)***
female_ratio	-1.228	-1.192	-1.042
	(0.421)***	(0.476)**	(0.454)**
constant	0.824	0.320	-0.391
	(0.352)**	(0.451)	(0.450)
σ_u^2	0.277	0.322	0.271
σ_v^2	0.013	0.018	0.016
$\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$	0.955	0.948	0.943
Log likelihood	282.802	269.083	287.031
N	1556	1549	1565