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Efficiency of Austrian Hospitals
An Application of Stochastic Frontier Analysis

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Abstract

The aim of this master's thesis is to evaluate inefficiencies in the Austrian hospital sector. In the first step a Stochastic Frontier Analysis is applied on a dataset which includes all hospitals which are funded by the state's health funds and which account for about 77% of Austrian hospital beds. The findings show that inefficiencies exist, which vary greatly between states and ownership structure. To get a better understanding of the applied technique a systematic comparison with another DEA study is applied. It is shown that the DEA constant returns to scale model is much more closely related to the SFA estimates than a variable returns to scale model. Still, the results on groups of hospitals are relatively stable regardless of which model or technique is applied.[1]

[1] I am grateful to my adviser Dr. Neil Foster for giving me the chance to write this thesis under his supervision and for his scientific support. I would also like to thank Thomas Czypionka, Markus Kraus, Markus Pock, Monika Riedel, and Gerald Röhrling from the IHS HealthEcon Team who were always there to discuss any problems that emerged during the work on this thesis.

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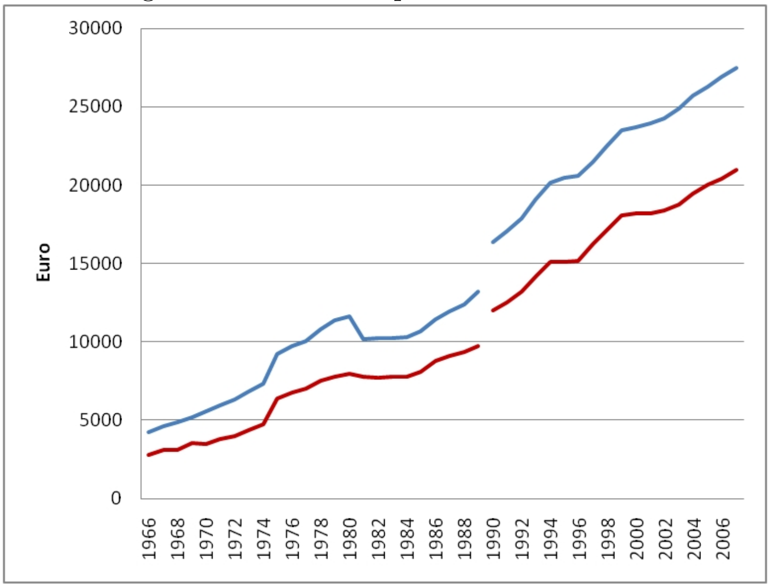
Chapter 1

Introduction

1.1 This Thesis

Countries all over the world have experienced a significant rise in health care expenditures over the last few decades. In Austria we observe a steep increase of public and private expenditures over time (see figure 1.1). The expenditures for hospitals have increased in a very similar way(see figure 1.3). Cost containment in health care is thus a very important topic on the agenda of most developed countries. Quality of care should on the other hand also not be forgotten. Public discussions about better quality in health care regularly take place. It is not an easy task to bring these two seemingly conflicting goals together. Higher quality will in general also be associated with higher costs. One way to maintain quality whilst cutting costs would be to increase the efficiency of health care providers. The first step here would be to identify the providers' inefficiencies and then to analyze them and to find out how they could be decreased. This master thesis aims to provide the first step of this process, the identification of inefficiencies in the Austrian hospital sector. The applied method is a Stochastic Frontier Analysis, which - although it is widely used in efficiency research in the U.S. and other countries - has never been applied to Austrian hospitals to the knowledge of the author. This thesis tries to bridge this gap and to identify driving forces of hospital efficiency in Austria.

Figure 1.1: Health Expenditures in Austria



expenditures in real terms

Source: OECD [2009], own compilation

The thesis proceeds in two steps: Firstly, two stochastic frontier analysis models are presented and interpreted in depth. These two represent the two preferred models, which are constructed following guidelines derived from the literature and considerations of the Austrian hospital system. Secondly, the results from another study which used Data Envelopment Analysis (DEA), another technique which is widely used in efficiency analysis, are compared with the SFA results. For this reason a third model is constructed which uses the same data and variables which are as close as possible to the DEA model.

For the first part, there are two main research questions:

- Does ownership matter for efficiency of Austrian hospitals?

- Are there regional differences in hospital efficiency?

In addition to variables capturing these aspects of Austrian hospitals we included a number of additional variables. These include the size of the hospital, the doctor ratio, administrative and operational staff ratio, and the occupancy rate. Economic theory and common sense suggests answers to some of the research questions addressed. We expect ownership to have an impact on the efficiency scores. This question has been addressed in recent research. Stochastic Frontier Analysis has been widely used on US hospital data and the question of ownership was at the core of many papers. Most papers were dealing more with the question of whether for profit hospitals are more efficient than non profit hospitals. As we will see later, we could not include for profit hospitals in our analysis. Still, the findings are mixed. Some authors find that non profit hospitals are more efficient (cf. Folland and Hofler [2001], Rosko et al. [2007], Rosko and Mutter [2008]), while other find that for profit hospitals are (cf. Li and Rosenman [2001], McKay and Deily [2005], Mutter and Rosko [2008]). As mentioned before, there are only a few studies on European hospitals. Herr [2008] found that public hospitals are the most efficient, while private non-profit hospitals were the least efficient. Farsi and Filippini [2008] who were using data on Swiss hospitals could not find significant differences in efficiency due to ownership.

For the second part of the analysis there is mainly one question: How does SFA perform compared to DEA? We will study whether the efficiency scores correlate between the two techniques. Some research on the differences between SFA and DEA results on hospitals has been done. Chirikos and Sear [2000] however were the only ones to attempt to get a deeper understanding of the differing results. In his dataset the Pearson correlation was always less than 0.4 and he found that DEA gives higher efficiency scores to bigger hospitals, while SFA gives higher scores to smaller hospitals. Jacobs [2001] found correlations between 0.4 and 0.6 and Linna and Häkkinen [1997] between 0.3 and 0.6.

1.2 Hospitals in Austria

In 2006 there were 264 hospitals registered in Austria with 63,354 beds altogether. These hospitals can be broadly split up into two groups: On the one hand there are the hospitals which are funded by the "Landesgesundheitsfonds" (the federal state's health funds, LGF). These are all *non-profit* hospitals. They are run either publicly or privately. These hospitals account for about 77% of all Austrian hospital beds. On the other hand there are some private *for-profit* hospitals. They are not funded by the "Landesgesundheitsfonds" and account for approximately 23% of all austrian hospital beds. In the following efficiency study we only include hospitals funded by the LGF. We had to limit this thesis to this smaller subset due to data availability and comparability. For a better understanding of the rest of the work it seems to be useful to have a closer look on the funding system of the LGF hospitals.[1]

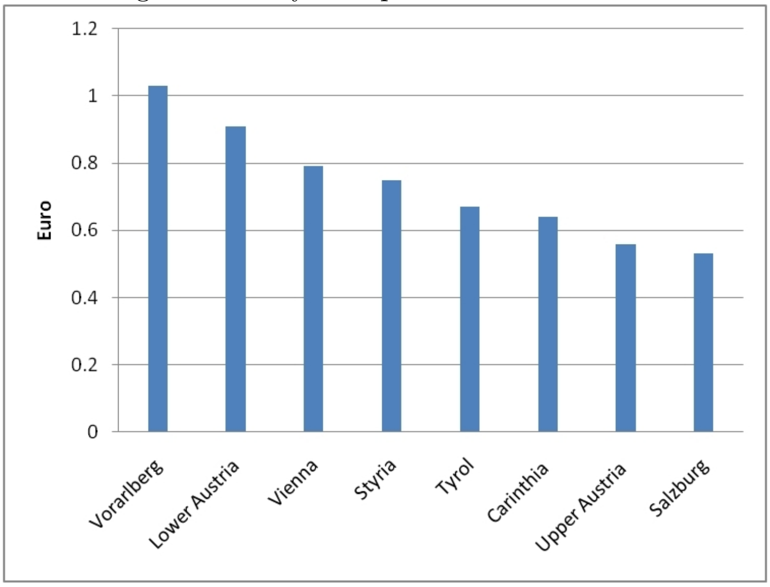
LGF hospitals are funded by various sources. The inpatient sector is mainly financed through the Austrian DRG system called *LKF*. This is a system of performance-oriented funding. Every inpatient service is given a specific amount of LKF points, which account for differences in costs of the provided services.

Every state has its own state health fund. These funds are financed from various sources (for example Social Insurance, the Federal Health Agency and different political bodies (tax based)). This system leads to differing budgets between the states. The value of the LKF points is calculated at the end of the year when all hospitals provide the state health funds with their LKF statistics. The formula is simply $\frac{\text{Budget allocated to the LKF system}}{\sum \text{LKF points}}$. This has two major implications:

[1] A detailed describtion of the system is available at `http://www.bmgfj.gv.at/cms/site/attachments/1/4/8/CH0718/CMS1098272734729/lkf-broschuere_internet.pdf` (available in German only)

- hospitals do not know the value of the LKF points while they are producing them
- The value of LKF points differ between states

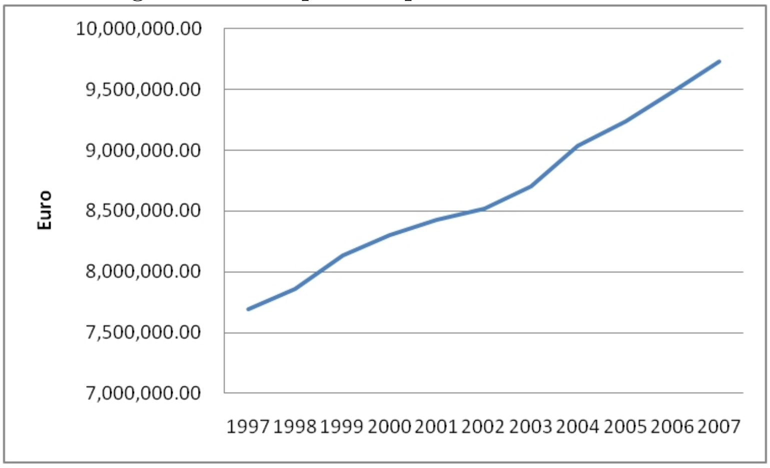
Figure 1.2: Payment per LKF Point in 2006



Source: Czypionka et al. [2008]

Figure 1.2 shows the differing LKF point values in the Austrian states for the year 2006. The value of one LKF point in Vorarlberg was nearly twice as much as one in Salzburg. While this is not the only reason that this system is sometimes criticized - other critique points include the fact that it is only applied to the inpatient and not the outpatient services and that the reimbursement does not suffice to cover all costs (cf. Czypionka et al. [2008, p.97]) - it has its merits and it does help a lot in this study. All Austrian hospitals funded by the LGF have to provide statistics about their services including the LKF points they have produced. This LKF statistic gives us a very good proxy of their inpatient activities which does not ignore the heterogeneity of possible outputs. As mentioned before, the LKF system does not apply to outpatient services. Here hospitals receive mainly some sort of flat payment which should enable them to maintain their outpatient department.

Figure 1.3: Hospital Expenditures in Austria



expenditures in real terms

Source: BMG [2010], own compilation

Chapter 2

Efficiency Analysis

This chapter starts by reviewing the concept of efficiency, more precisely cost efficiency, before describing the most popular econometric tool for finding efficiency scores, *Stochastic Frontier Analysis*, in depth.

2.1 Efficiency

In neoclassical economics, firms are generally assumed to be profit maximizing. This leads to the assumption that producers are successful in solving their optimization problem, ie. they are either cost minimizing given a level of output or output maximizing given a level of input. Although this is a useful, sometimes even necessary, assumption, we don't observe perfectly successful optimizers in reality.

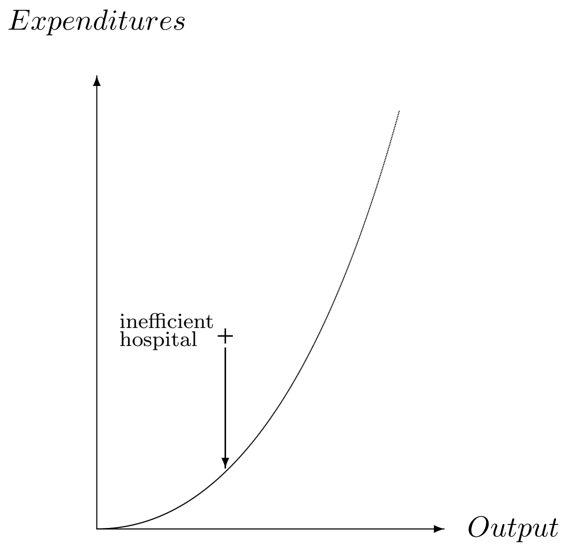
We can differentiate between two kinds of efficiency. The first one, production efficiency, refers to output maximization. Cost efficiency, on the other hand, assumes that firms cannot maximize their outputs, because they can't influence demand. So given their level of outputs they have to try to reduce costs as far as possible.

We will take a closer look at the efficiency of hospitals. We can assume that hospitals face a given amount of demand for medical services, which they cannot influence. Given this assumption, an efficiency analysis of hospitals has to be based on cost efficiency. Although this might not seem as a strong assumption, there are reasons why it actually may be so. The empirical literature suggests that there is actually some supplier induced demand in health care, cf. for example Liao and Detroit [2009] and Busato et al. [2009]. Nevertheless it still seems more plausible to use this assumption and address this supplier induced demand by checking for endogeneity of the outputs. Figure 2.1 provides some intuition about cost efficiency. The curve depicts the cost efficiency curve, the *cost frontier*. Firms, or in our case hospitals, which operate on this curve can be seen as cost efficient. Given their output they have minimized their costs. Hospitals which lie above the curve can be called inefficient. They could reduce costs and still produce the same amount of output. The cost frontier is not observed in reality and needs thus to be estimated. Over time many different techniques have been developed to measure inefficiencies. Lovell [1993] gives an overview of these and shows how they evolved over time. Nowadays two methods are widely used in applied research: *Data Envelopment Analysis (DEA)*, a non-parametric method, and *Stochastic Frontier Analysis (SFA)*, a parametric method. We will come back to Data Envelopment Analysis when we compare the findings of this analysis with a research report of the Institute of Advanced Studies, which used a DEA method to evaluate the efficiency of Austrian hospitals. Since we are only using a Stochastic Frontier method for our analysis, we will for now concentrate on this method.

2.2 Stochastic Frontier Analysis

In this section we will give a short introduction to the Stochastic Frontier Analysis. The derivation of the stochastic frontier analysis will primarily be based on Kumbhakar and Lovell [2000]: *"Stochastic Frontier Analysis"*

Figure 2.1: Cost Efficiency



and Coelli et al. [2005]: *"An Introduction to Efficiency and Productivity Analysis"*.

In 1977 two papers with very similar content were published. They can be seen as the beginning of SFA as we use it today. Meeusen and van Den Broeck [1977] published their article just shortly before Aigner et al. [1977]. These two papers were the first to introduce Stochastic Frontier Analysis with its core idea: the composed error term. Since then many additions have been made. Kumbhakar and Lovell [2000] give a good overview of how the method developed over time. For our purpose it seems to be more useful to give a short introduction to the analytical foundations and basics of the SFA. For a more detailed description please refer to Kumbhakar and Lovell [2000].

A cost frontier can be written as:

$$E_i \geq c(y_i, w_i; \beta), \qquad i = 1, \dots, I, \tag{2.1}$$

where $E_i = w_i^T x_i = \sum_n w_{ni} x_{ni}$ are firm i's expenditures, firm i's outputs are given by $y_i = (y_{1i}, \dots, y_{Mi}) \geq 0$ and β is a vector of technology parameters.

Expenditures are greater or equal to the minimum feasible costs, $c(y_i, w_i; \beta)$, which is thus the cost frontier common to all producers. This formulation of the cost frontier is deterministic. From this the computation of the cost efficiency follows easily.

$$CE_i = \frac{c(y_i, w_i; \beta)}{E_i}, \tag{2.2}$$

Cost efficiency is the ratio of minimum feasible costs to the actual expenditures. Equation 2.2 assigns all deviation from the cost frontier as inefficiencies. For an econometric application we must allow for random statistical noise in the data. If we include this noise term in the function we arrive at this formulation of cost efficiency:

$$CE_i = \frac{c(y_i, w_i; \beta) \cdot exp\{v_i\}}{E_i}, \tag{2.3}$$

where $exp\{v_i\}$ are random shocks. A stochastic cost frontier model following a Cobb-Douglas cost frontier can thus be formulated:

$$\ln E_i \geq \beta_0 + \beta_y \ln y_i + \sum_n \beta_n \ln w_{ni} + v_i + u_i, \tag{2.4}$$

where $CE_i = exp\{-u_i\}$. Here we observe for the first time one of the key characteristics of SFA: the *composed error term* which consists of statistical noise (v_i) and the inefficiency term (u_i). This composed error term ($\epsilon_i = v_i + u_i$) is asymmetric, positively skewed since the inefficiency term u_i has to be ≥ 0. This term can be both an advantage and disadvantage over other methods. While it gives the possibility to account for random noise in the data (something which is not possible using DEA for instance), it raises the question of how this composed error term is distributed. There is no *a priori* justification for one specific distribution. Kumbhakar and Lovell [2000] give an overview of four different possible distributions: Normal-Half Normal, Normal-Exponential, Normal-Truncated Normal, Normal-Gamma. All four distributions assume v_i to be distributed normally ($v_i \sim$ iid $N(0, \sigma_v^2)$), while they make different assumptions about the distribution of u_i, the efficiency term. There exist many more possible density distributions, but these four are by far the most common in applied resarch. To give some intuition on how these distributions look, we now derive the Normal-Half Normal distribution. This derivation follows Kumbhakar and Lovell [2000].

The following assumptions concerning the distributions are made:

(i) $v_i \sim$ iid $N(0, \sigma_v^2)$

(ii) $u_i \sim$ iid $N^+(0, \sigma_u^2)$

(iii) v_i and u_i are distributed independently of each other, and of the regressors

Assumption (i) is the distribution of the random noise, the normal distribution. Assumption (ii) is the distribution of the inefficiency. Inefficiencies can only be positive and therefore it is plausible to assume that they are half-normally (non-negative) distributed. The density functions of $u_i \geq 0$ and v_i are:

$$f(u) = \frac{2}{\sqrt{2\pi}\sigma_u} \cdot exp\left\{ - \frac{u^2}{2\sigma_u^2} \right\} \tag{2.5}$$

and

$$f(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \cdot exp\left\{ - \frac{v^2}{2\sigma_v^2} \right\}. \tag{2.6}$$

Given assumption (iii) the joint densitiy function follows:

$$f(u, v) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot exp\left\{ - \frac{u^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2} \right\}. \tag{2.7}$$

The joint error term is given by $\epsilon = u + v$ and the joint density function for u and ϵ can be formulated:

$$f(u, \epsilon) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot exp\left\{ - \frac{u^2}{2\sigma_u^2} - \frac{(\epsilon - u)^2}{2\sigma_v^2} \right\}. \tag{2.8}$$

By integrating u out of equation 2.8 we derive the marginal density function of ϵ

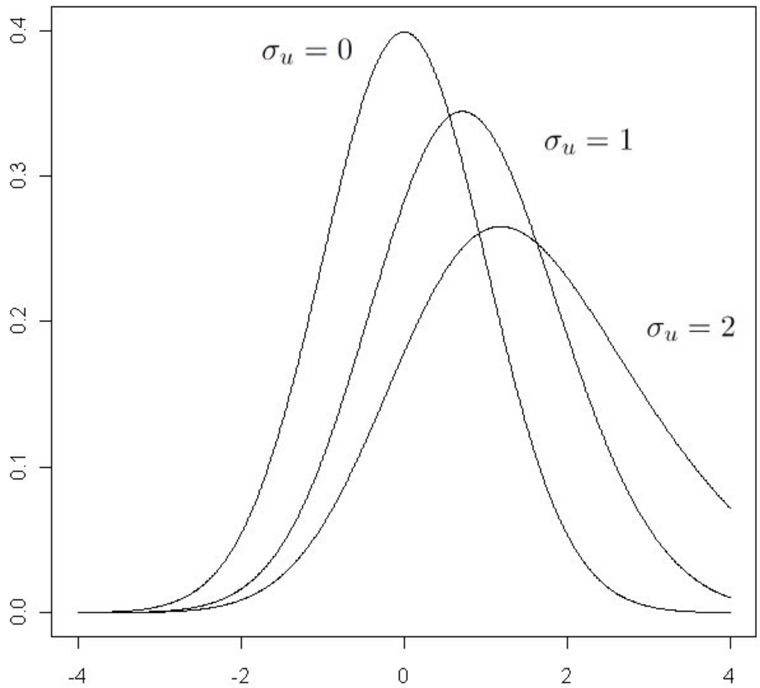
$$\begin{aligned} f(\epsilon) &= \int_0^\infty f(u,\epsilon)du \\ &= \frac{2}{\sqrt{2\pi}\sigma} \cdot \left[1 - \Phi\left(\frac{-\epsilon\lambda}{\sigma}\right)\right] \cdot exp\left\{-\frac{\epsilon^2}{2\sigma^2}\right\} \\ &= \frac{2}{\sigma} \cdot \phi\left(\frac{\epsilon}{\sigma}\right) \cdot \Phi\left(\frac{\epsilon\lambda}{\sigma}\right), \end{aligned} \tag{2.9}$$

where $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$, $\lambda = \frac{\sigma_u}{\sigma_v}$, and $\Phi(\cdot)$ and $\phi(\cdot)$ are the standard normal cumulative distribution and density functions. If $\sigma_u \to 0$ or $\sigma_v \to \infty$ then $\lambda \to \infty$. This means that the random error term dominates the efficiency term and the cost frontier model collapses to an OLS cost function. If we have the opposite case, namely $\sigma_u \to \infty$ or $\sigma_v \to 0$ then $\lambda \to 0$. In this case there is no statistical noise and all deviation from the cost frontier is reflected in the inefficiency term. Figure 2.2 shows what the graph of this distribution looks like for different values of σ_u. The efficiency value will be defined as $exp(-U_i)$. The efficiency scores will lie between 1 and ∞. To arrive at a percentage score we consider the reciprocal.

2.3 Strengths and Weaknesses of SFA

Clearly SFA is a very interesting and relatively new technique, but it still has its weaknesses. It seems to be important to describe the strengths and the limits, only then is it possible to really interpret the results correctly. Newhouse [1994] is in general very skeptic of the explanatory power of any existing frontier method. “I am doubtful that the regulator can recover ‘true’ or efficient cost or production parameters from observed data with any degree of precision.” He bases this on several arguments, some of which have now been addressed. He emphasizes the heterogeneous nature of hospital output and quality, which will bias the efficiency scores if not taken into account. The second major critique point is that there is no *a priori*

Figure 2.2: Normal - Half Normal Distribution with $\sigma_v = 1$



justification of a specific error distribution. A wrong choice will also bias the outcome. Although the distributional assumptions of the error term can be seen as a weakness, the composed error term itself is a big advantage over other techniques. It accounts for statistical noise and measurement errors in the data, something other frontier methods are not able to do, cf. Sarafidis [2002, p. 10]. Coelli et al. [2005, p. 312] and Dlouhỳ [2009, p. 183] mention the possibility of conducting hypothesis tests as another advantage over other techniques. The model specification and the model selection can be tested. Overall Jacobs [2001, p. 113] concludes that "given cross-sectional data, these techniques [DEA and SFA, author's note] are certainly some of the better methodological approaches available". But the method should only be used as a signaling device. "The different efficiency scores should not (...) be interpreted as accurate point estimates of efficiency, but might more usefully be interpreted as indicating general trends in inefficiency for certain Trusts."

Chapter 3

Application

We use a sample of 133 Austrian hospitals in the year 2006 for our analysis. These 133 hospitals are all Austrian hospitals funded by the "Landesgesundheitsfonds" (LGF, the provincial health funds). This means that about 131 hospitals not funded by the LGF are not included in this study. These are privately ('for-profit') run hospitals, which had to be excluded because of data availability. Nevertheless, the hospitals in our data sample account for 77% of all hospital beds in Austria. Hospitals funded by the Landesgesundheitsfonds are run by different operators, most of which are operated by the states or municipalites with others operated by congregations or other confessional carriers. Table 3.1 gives an overview of the hospitals by state and carrier. Most of the LGF-hospitals are run by the states. The group of 'other non-confessional providers' includes all hospitals that are run for example by health insurances, foundations, private persons, and so on. The boxplots in figure 3.1 indicate that state run hospitals are in general bigger than other hospitals.

Table 3.1: Data Structure

Provider	State									Tot
	Bgl	Ktn	Noe	Ooe	Sbg	Stm	Tir	Vbg	W	
St	4	5	15	11	3	19	4	5	12	78
Mu	0	0	4	1	5	0	7	1	0	18
Cong	1	3	0	8	2	4	1	0	8	27
Non-Conf	0	1	0	0	0	2	0	1	2	6
Conf	0	2	0	0	0	1	0	0	1	4
Tot	5	11	19	20	10	26	12	7	23	133

St: State, Mu: Municipality, Cong: Congregation, Non-conf: Other non-confessional, Conf: Other confessional

Bgl: Burgenland, Ktn: Carinthia, Noe: Lower Austria, Ooe: Upper Austria, Sbg: Salzburg,

Stm: Styria, Tir: Tyrol, Vbg: Vorarlberg, W: Vienna

3.1 Part I – SFA

This part of the thesis concentrates on the different possible ways of constructing SFA models. Finally the two preferred models are estimated and presented.

3.1.1 Model specification

When looking at hospitals it is useful to think of them as cost minimizers rather than output maximizers. can assume that hospitals are facing a given number of cases, which they can't really influence. For this reason we are looking only at cost-efficiency in this study. To our knowledge all studies on hospital efficiency concentrate on the cost-side. The main research question is whether whether specific hospital characteristics influence the efficiency score of every hospital. Are there regional differences? Does ownership matter?

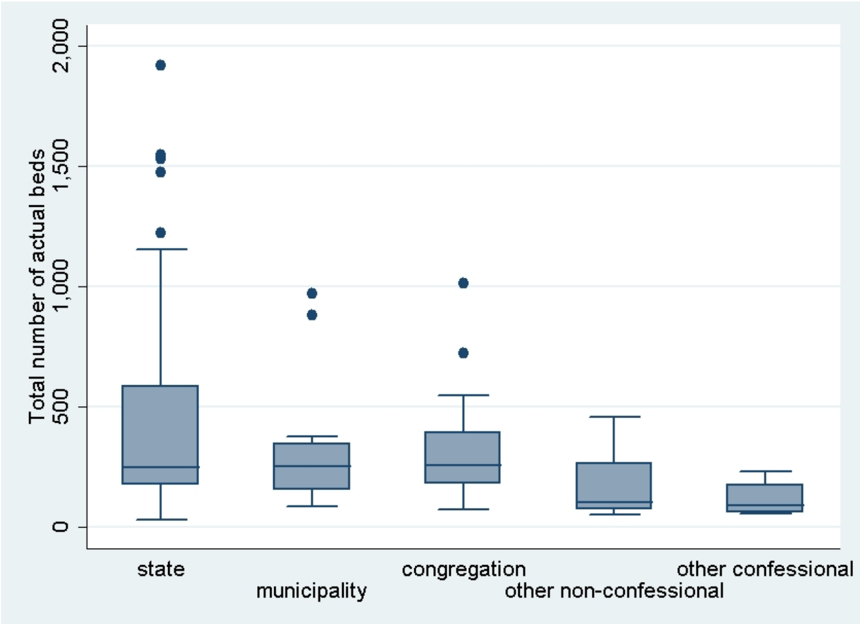


Figure 3.1: Hospital Size

Variable Selection As usual variable selection is of great importance. To get a better feeling for this problem it is useful to see what other researchers have done. Rosko and Mutter [2008] give an excellent overview of other SFA applications to U.S. hospital data. They find that variable selection is fairly similar across all reviewed studies. All studies included total expenditures on the right hand side. Most of them deflated them by the wage rate or the capital cost. Wage rates were typically calculated by dividing the payroll expenses by the full time equivalent personnel. The cost of capital is in most cases constructed by dividing the sum of depreciation and interest expenses by the total number of beds in the hospital. Outputs were usually given by some measure of outpatient activity and inpatient activity. Almost all studies tried to include at least some sort of structural indicator of quality into the frontier estimation. For reasons of data availability this was done by including a dummy variable indicating whether hospitals are teaching hospitals or not. Some studies also included outcome measures of quality such as risk adjusted mortality rates. This is the basic setup in almost all studies. Some authors included more variables and controlled for example for different wage rates by group of personnel in the hospitals, cf. eg. Chirikos and Sear [2000].

Functional Form As with most papers on hospital efficiency we consider both *Cobb-Douglas* and *Translog* functions. Both types of production and cost functions have their own merits. Cobb Douglas functions are relatively easy to compute due to the very few coefficients that have to be estimated. Cobb-Douglas functions cannot be used to account for multiple outputs however cf. Kumbhakar and Lovell [2000, p. 143]. A Translog function gives much more flexibility. It allows for multiple outputs and includes all cross-terms. On the other hand the model can become relatively large with a lot of coefficients to be estimated. With our limited sample of only 133 hospitals and thus an already limited amount of degrees of freedom this can easily become a big problem. So it is not surprising that some translog models failed to converge. The Cobb-Douglas function can be seen as a special case of the Translog function, where all the cross-products and squares are equal to zero. Therefore it is possible to conduct likelihood ratio tests to decide which one of the two functions is more appropriate given the available data. The specification of the log linear Cobb-Douglas cost function is given on page 14. The translog model is richer and given by:

$$\begin{aligned}\ln E_i \geq \alpha_0 &+ \sum_m \beta_m \ln y_{mi} + \sum_n \beta_n \ln w_{ni} + \frac{1}{2}\sum_m \sum_j \delta_{mj} \ln y_{mi} \ln y_{ji} \\ &+ \frac{1}{2}\sum_n \sum_k \delta_{nk} \ln w_{ni} \ln w_{ki} + \frac{1}{2}\sum_n \sum_m \delta_{nm} \ln w_{ni} \ln y_{mi} + v_i + u_i,\end{aligned} \tag{3.1}$$

To satisfy the homogeneity assumption we have to divide the input prices and the total expenditures by one input price. The choice of the input price here is arbitrary, the choice itself will not change the results.

$$\ln \frac{E_i}{w_{li}} \geq \alpha_0 + \sum_m \beta_m \ln y_{mi} + \sum_{n \neq l} \beta_n \ln \frac{w_{ni}}{w_{li}} + \frac{1}{2} \sum_m \sum_j \delta_{mj} \ln y_{mi} \ln y_{ji}$$
$$+ \frac{1}{2} \sum_{n \neq l} \sum_{k \neq l} \delta_{nk} \ln \frac{w_{ni}}{w_{li}} \ln \frac{w_{ki}}{w_{li}} + \frac{1}{2} \sum_{n \neq l} \sum_m \delta_{nm} \ln \frac{w_{ni}}{w_{li}} \ln y_{mi} + v_i + u_i, \tag{3.2}$$

Distribution of the composed error term The next choice to make is on the distribution of the composed error term. In principal there are almost infinite possible distributions which one could use for the composed error term. In applied research at least three distributions are often used: Normal – Half Normal, Normal – Truncated Normal and Normal – Exponential. A Normal – Gamma distribution is also discussed in the literature, but to our knowledge there has not been a single study on hospital efficiency using this distribution. This could be the case because it is not yet implemented in either STATA or Frontier (the program which we will be using for our estimations). On the other hand there are also theoretical considerations which may lead to the choice of another distribution. Ritter and Simar [1997] argue against this distribution if the sample size is not very large, which is unfortunately the case in our sample of 133 hospitals. "We fear that the normal-gamma model and probably other free-shape models aimed at estimating frontiers and inefficiencies from small to medium sized samples may not form the basis of valid measurement processes." [Ritter and Simar, 1997, p. 182]. The use of Normal – Exponential is also not very common among health economists. Rosko and Mutter [2008] found in their meta analysis of SFA applications on hospital data only 4 studies which used this distribution. Since this distribution is also not included in the Frontier program and the relatively scarce use of it, we decided to concentrate on the Normal – Half Normal and the Normal – Truncated Normal distributions. The Normal – Half Normal distribution has the merit of being relatively easy to compute (it is fix-shaped), while the Normal – Truncated Normal distribution is more flexible. It is also interesting to see that the former distribution is a special (nested) case of the latter, which means that we can apply formal hypothesis testing in the form of a likelihood ratio test to determine which of the two distributions is more appropriate given the data and the functional form.

The chosen distribution of the composed error term will nevertheless be prone to the critique of being arbitrary, but while this has to be acknowledged it may actually not be such a big problem after all. Some studies have shown that the selection of the distribution had in the end only a very small impact on the estimated results (cf. Zuckerman et al. [1994] and Rosko [2001]).

Estimation Procedure Finally a decision on the estimation procedure had to be made. It is possible to estimate the efficiency scores and their inefficiency effects variables in a one stage or two stage procedure. In the two stage procedure one basically calculates efficiency scores in the first stage and uses a Tobit regression on these efficiency scores in the second stage. Although this procedure has been used in applied research, a one stage procedure is generally preferred. The one stage estimation has several advantages over the two stage estimation, as Wang and Schmidt [2002, p. 140] describe in their paper. Results derived from the two stage estimation process are less efficient leading to more coefficients that are not significant. Even worse, the results are biased. There is also one other reason on theoretical grounds why the two stage estimation should not be used: When the cost frontier is estimated in the first stage, the inefficiency scores are in the composed error term and are thus assumed to be random. Then in the second step they are seen as if they can be explained by other variables. It violates thus one of the key assumptions. Overall the one step procedure, and more precisely the Battese and Coelli [1993] specification, is highly preferred over the two stage procedure and will thus be used for our estimations.

3.1.2 The two models

In the following section we will present the results of two different models. Each of which has its own merits and shall be introduced by the following table:

Model 1 production function: Translog; Output: LKF-Points; Input prices: hospital specific wage rate, hospital specific capital cost rate; structural quality indicator: university hospital; distribution of the error term: Normal – Truncated Normal

Model 2 production function: Translog; Output: LKF-Points, Total Number of Out-Patients; Input prices: hospital specific wage rate, hospital specific capital cost rate; structural quality indicator: university hospital; distribution of the error term: Normal – Truncated Normal

Model 1: One Output This model only includes the hospitals' inpatient activities. There are two reasons for including such a model which does not include all hospital outputs. It allows for a relatively simple model. In principal a Cobb-Douglas production function would be possible to assume (although the likelihood test rejected it). Because the outpatient section is in general small compared to the rest of the hospital it is also plausible to assume that most differences between hospitals lie in the inpatient section. So looking at the inpatient services only has the potential to identify problems in the most important part of the hospital using a less difficult model.

Since data is available on inpatient sections of the hospitals it is a good opportunity to evaluate them.

Following the above reasoning, decisions had to be made about the included variables, the functional form, and the estimation technique. In this case the aim was to present a relatively small model, which is easy to interpret. Therefore only four explanatory variables were taken into account: two wage rates, the price of capital and a dummy variable indicating whether the hospital is a university hospital or not. The variables are constructed analogously to the literature: the wage rates are calculated by dividing the total hospital expenditures on the personnel group by the total number of FTE personnel, the price of capital is simply the capital expenditures divided by the total number of beds. This university variable serves as the structural quality indicator. There are also more hospitals in Austria which are involved in teaching activities, but no data could be found on the amount of teaching activity for every specific hospital. Therefore it is safer to include only a dummy variable for university hospitals. They provide most of the teaching. Expenditures and input prices were normalized by dividing them by the doctors' wage rate. Translog was chosen as the functional form. This was tested against and preferred over Cobb-Douglas using a likelihood ratio test ($H_0 : \delta_1 = \delta_2 = \delta_3 = 0$). Furthermore likelihood ratio tests were conducted to find out that SFA is preferred over OLS ($H_0 : \gamma = 0$) and that the Normal-Truncated Normal is preferred over the Normal-Half Normal($H_0 : \mu = 0$). The test statistics follow a χ^2-distribution, only the test of $\gamma = 0$ follows a mixed χ^2-distribution. The test statistics for this distribution can be found in Kodde and Palm [1986]. The Test statistics are documented in Table 3.3.

Model 2: Two Outputs Here outpatient services are also included in the model. So compared to model 1 we are now looking at all hospital outputs, which thus creates a full picture. For reasons of data availability it was not possible to give different weights to the differing outpatient activities of a hospital and thus construct something like the LKF system. Although this would have been preferable given the heterogeneity of possible outpatient outputs, it is probably not such a big problem. There might well be some outpatient outputs which are much more expensive to produce than others, but since outpatients only come to the hospital to get a short treatment and leave afterwards, it seems that the heterogeneity is much less of a problem here compared to the inpatient sector. The other variables are constructed analogously to model 1. Again likelihood ratio tests were conducted to justify the use of SFA ($H_0 : \gamma = 0$) and the Normal-Truncated Normal distribution ($H_0 : \mu = 0$) and the results can be found in Table 3.5. There is no need to test the appropriateness of the Translog function since it is in any case preferred over Cobb-Douglas when multiple outputs are involved. After checking the data for consistency one hospital had to be dropped from the sample, because of obvious errors in the data on outpatient services.

3.1.3 Results

The results were computed using the Frontier 4.1 program[1].

Model 1 Table 3.2 gives the results from model 1. The value of γ, which is defined as $\gamma = \frac{\sigma_u^2}{\sigma_v^2+\sigma_u^2}$, has to be ≤ 1. A small value indicates that statistical noise is the main driver between hospitals, a large value indicates that inefficiencies dominate the statistical noise. In this case we observe a value of 0.39 which tells us that both factors are important for this data set. The first seven coefficients (intercept + 6 other variables) are the results from the frontier estimation. Surprisingly the university hospital variable did not

[1] Frontier is a freeware computer program written by Tim Coelli and is available at the CEPA homepage.

Table 3.2: Estimation Results Model 1

Variable	**Coefficient**	**SE.**
Intercept	3.463*	(1.473)
LKF	-0.535**	(0.172)
Capital price	1.323**	(0.391)
LKF sq	0.083**	(0.010)
Capital price sq	0.086	(0.056)
LKF * capital price	-0.065**	(0.021)
University hospital	0.084	(0.061)
Intercept	1.057**	(0.304)
Municipality	-0.149	(0.1389)
Congregation	-0.213**	(0.062)
Confession	0.099	(0.119)
Other	-0.339**	(0.058)
Burgenland	-0.194†	(0.110)
Carinthia	-0.919**	(0.120)
Lower A	-0.448**	(0.109)
Upper A	-0.383**	(0.072)
Salzburg	-0.296*	(0.122)
Styria	-0.275**	(0.063)
Tyrol	-0.778**	(0.172)
Vorarlberg	-0.278**	(0.101)
Special hospital	0.177*	(0.070)
Doctors / staff	-2.466**	(0.854)
Operational staff / staff	-0.282	(0.590)
Beds	0.000	(0.000)
Patient days / bed	0.000	(0.001)
σ^2	0.019**	(0.003)
γ	0.386**	(0.094)
Log likelihood		**93.77**

Significance levels : † : 10% $*$: 5% $**$: 1%

base group: Viennese state run hospitals, which are not 'special hospitals'

Please refer to the Appendix for exact definitions of the variables.

Table 3.3: Likelihood Ratio Tests Model 1

Null Hypothesis	Test Statistics	Critical Value	Decision
$\mu = 0$	11.71	3.84	reject
$\gamma = 0$	113.96	5.14	reject
$\delta_1 = \delta_2 = \delta_3 = 0$	10.27	7.81	reject

enter significantly into the model. The output measure (LKF) and the remaining input price, capital [2], are highly significant and have the expected signs. The second part of Table 3.2 shows the results of the inefficiency explanatory variables. We observe that there are indeed differences in the efficiency scores between different ownership forms and regions. Concerning ownership we see that with state run hospitals as the base group congregational and other privately run non-profit hospitals are more efficient than public hospitals (run by the states or the municipalities). Other confessional hospitals which are not run directly by congregations are not significantly different to public hospitals. Regional differences are also clearly visible. With Vienna as the 'base-state' we can see that hospitals in basically all other states are run more efficiently. From the last five variables only two enter the model significantly. we chose to include the variable 'special hospital', to look at a very specific kind of hospitals. These are hospitals that provide only services related to a specific health problem and they are generally smaller (the average size is 247 beds compared to an average of 367 for all Austrian LGF hospitals). we were expecting these hospitals to be more efficient than the rest, but it turned out that they are significantly worse in this data sample and model.

Model 2 Model 2 includes outpatient services as a second hospital output. In this case the value of γ increases to 0.65. This indicates that

[2] remember: the wage rate does not appear anymore since it was the chosen input price which was used to harmonize the other prices and total expenditures.

Table 3.4: Estimation Results Model 2

Variable	Coefficient	SE.
Intercept	26.271**	(1.805)
LKF	-3.494**	(0.385)
Outpatients	1.083**	(0.378)
Capital price	1.579*	(0.793)
LKFsq	0.285**	(0.042)
Outpatients sq	-0.005	(0.032)
Capital price sq	-0.048†	(0.025)
LKF * OutPatients	-0.055	(0.035)
LKF * capital price	-0.097	(0.070)
OutPatients * capital price	0.064	(0.53)
University hospital	0.058	(0.069)
Intercept	0.917**	(0.286)
Municipality	-0.005	(0.118)
Congregation	-0.583**	(0.092)
Confession	-0.024	(0.157)
Other	-0.579**	(0.174)
Burgenland	-0.480**	(0.178)
Carinthia	-0.563**	(0.160)
Lower A	-0.695**	(0.155)
Upper A	-0.514**	(0.098)
Salzburg	-0.629**	(0.165)
Styria	-0.398**	(0.092)
Tyrol	-1.113**	(0.181)
Vorarlberg	-0.387**	(0.147)
Special hospitals	0.166	(0.111)
Doctors / staff	-4.189**	(1.187)
Operational staff / staff	1.926*	(0.831)
Beds	0.000	(0.000)
Outpatients / LKF	-0.038	(1.001)
Patient days / bed	-0.002	(0.001)
σ^2	0.022**	(0.005)
γ	0.645**	(0.107)
Log likelihood		**92.67**

Significance levels : † : 10% $*$: 5% $**$: 1%

base group: Viennese state run hospitals, which are not ‘special hospitals’

Please refer to the Appendix for exact definitions of the variables.

Table 3.5: Likelihood Ratio Tests Model 2

Null Hypothesis	Test Statistics	Critical Value	Decision
$\mu = 0$	22.19	3.84	reject
$\gamma = 0$	134.06	5.14	reject

both statistical noise and inefficiencies are still present, but that the differences between hospitals are driven more by inefficiencies in this model when compared with model 1. The frontier estimation gives again plausible coefficients. The university hospital variable still does not enter the model significantly. One thing to note on the inefficiency explanatory variables is that the coefficients of the significant variables is in absolute terms greater in the second model compared to the first. But in general we can see that the results are relatively stable with the signs of the coefficients being consistent across models. The group of 'other' hospitals and hospitals which are run by congregations are still significantly more efficient than their public counterparts. But while in model 1 the group of 'other' hospitals was the most efficient they are now basically the same as congregational hospitals. Regional differences are still observable and all states are significantly associated with higher efficiency scores than Vienna. The greater the doctor ratio in the total staff, the more efficient hospitals are. Interestingly the ratio of administrative and operational staff is now also significant with the expected sign. The higher the percentage of such personnel in total staff, the less efficient the hospital is. In this second model there is no significant difference anymore between 'special' hospitals and the rest.

Comparison A comparison of the two estimated models reveals that the results are very stable. This supports the assumption that was made when we introduced model 1: that most of the existing inefficiencies can be explained by the inpatient section alone. Table 3.6 shows that the Mean, Minimum, and Maximum efficiency estimates are basically the same in the two models. The hospitals seem to perform a little worse in the second model, but this difference is so small that it is negligible. Table 3.7 supports these findings. Not only the inefficiency effects variables turn out to be stable between the two models, but also the individual estimations are very closely related to each other. A Pearson correlation of 0.89 indicates a high level of consistency.

Table 3.6: Comparison Model 1 - Model 2

Model	Obs	Mean	Median	SD	CV	Min	Max
1	133	0.868	0.908	0.117	0.135	0.498	0.991
2	132	0.847	0.888	0.133	0.157	0.437	0.989

Table 3.7: Person and Spearman Correlations

	Model 1
Model2	0.886
	0.813

first row: Pearson, second row: Spearman

3.1.4 Limitations

This work has three major limitations:

1. Endogeneity problems?
2. No real quality indicator
3. Are not for profit hospitals cost minimizing?

Endogeneity

> "The price of labor can be measured in various ways. If the quantity is measured using the number of employees or hours worked,

> then a common approach is to measure the price of labor of each firm as the total labor costs divided by the quantity measure. This implicit labor price will pick up geographical differences in wages, assuming constant labor quality across firms; however, if labor quality (skill mix and so on) is not constant across firms, the quantity and price measures will be biased". [Coelli et al., 2003, p. 85]

Endogeneity is usually a great concern of every econometrician. It is known that models estimated with endogenous variables will return biased results, if the endogeneity is not accounted for. In the case of frontier estimation there are several possible endogenous variables included in our analysis. This starts with output quantities and ends with input prices. Only very few studies of hospital efficiency address this problem. The reason for this is probably that it is very difficult to find suitable instruments which could then be used instead of the endogenous variables. At least there were no good instruments available for this study. Most instruments that we tried were very weakly correlated with the concerning variable. Bound et al. [1995] show that the use of weak instruments may do more harm than the original endogeneity bias. For this reason we decided to not use instrumental variables. Another possible way to avoid endogeneity (or to at least weaken it) would be to construct the input prices in a different way. Having calculated already the hospital specific input prices it is only a small step towards taking the state average price of every input. This construction of the prices necessarily leads to a loss of information in the data, but should help in decreasing the endogeneity induced bias. The results were actually not to bad. The coefficients of the significant variables pointed in the same direction and were of comparable signs. But since the models with the newly constructed prices also led to less significant results we finally decided to not follow this approach. So finally we have to accept that there might be a potential for bias in the estimation results.

Quality indicator This study lacks a real outcome oriented quality indicator. The teaching indicator can serve as a structural indicator, but this is by no means a good substitution for a real quality outcome measure. First of all, just because hospitals have this structural advantage does not necessarily mean that they produce higher quality care than other hospitals. Secondly, only fourteen hospitals in this sample are teaching hospitals. The problem of excluding a quality indicator is easily explained: high quality is associated with higher costs. If we do not control for quality we run the risk of interpreting higher quality as a higher inefficiency. This is surely not desirable. The findings in the literature about the effects of including or not including outcome measures of quality are mixed. Mutter et al. [2008] find that the mean in-effiency in their data set drops from 17.3% to just 14.2% when they include several quality measures. While this is undisputed it is also interesting to see if some hospitals really change their efficiencies compared to others, i.e. does the impact of quality measures lead to a different ranking? The authors find a Pearson correlation of at least 0.8 between the estimated models indicating some minor changes. Rosko and Mutter [2008] on the other hand find that the impact of outcome measures is relatively small: "including these variables [outcome measures of quality, author's note] had a minimal impact on inefficiency estimates". Nevertheless they argue in favor of including them:"We found that outcome measures of quality belonged in the hospital cost function model".

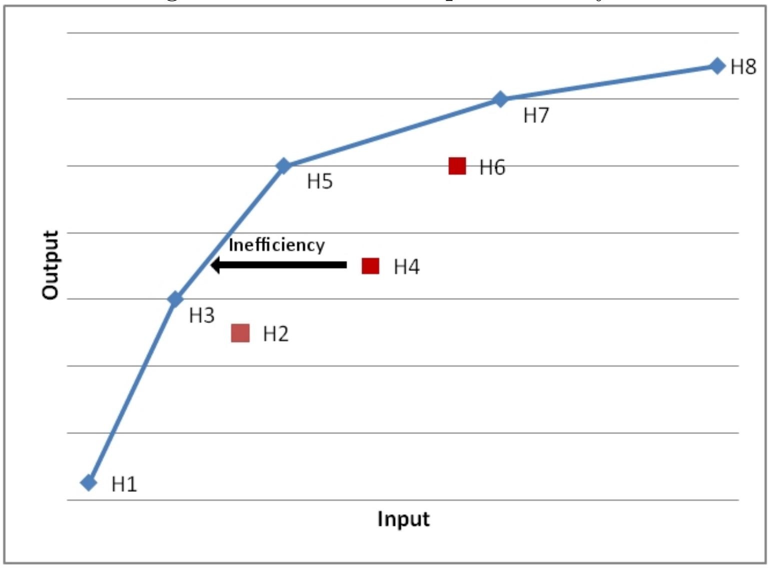
Are hospitals cost minimizing? This question touches a core problem when evaluating the cost efficiency of Austrian non-profit hospitals. Is it reasonable to calculate these efficiency scores, even if hospitals are not trying to be efficient? There are in fact only weak regulatory incentives for the hospitals to cut their costs. Nevertheless we find this not a real objection of conducting such analyses. It is important to point out this lack of incentives. One possible way is basically to conduct such studies of efficiency to point out this problem.

Discussion Despite these three limitations we still find the models to be valid. The main findings are very stable. As pointed out before (see section 2.3 on page 16) it is important not to emphasize the point estimations too strongly but rather interpret groups of hospitals. Our analysis shows that there are important regional and other differences in efficiency scores. The findings are stable in all estimated models and can therefore be seen as valid.

3.2 Part II - Comparison of DEA and SFA Estimations

Besides Stochastic Frontier Analysis there is a second technique which is widely used in applied research on efficiency, *Data Envelopment Analysis*, DEA. While SFA relies on econometrics and regression analysis, DEA uses linear programming and results are achieved by solving a mathematical maximization problem. For the mathematical derivation of DEA please refer for example to Coelli et al. [2005]. Figure 3.2 shows what the results from DEA calculations look like. In this simplistic case there is only one type of input and one type of output. Hospitals which lie on the frontier can be called efficient. The way in which the DEA is calculated necessarily will lead to the result that some hospitals (at least one) are 100% efficient. Hospitals which lie to the right of the curve are inefficient because they need more of the input to produce a given level of output. Efficiency is thus again only a concept which is relative to other existing hospitals.

Figure 3.2: Data Envelopment Analysis



3.2.1 SFA vs. DEA

While the weaknesses and strengths of SFA have already been discussed above, we will have a closer look at DEA here. Coelli et al. [2005] finds the following advantages of DEA over SFA:

- There is no need to make assumptions about the distributional form of the inefficiency term
- There is no need to make assumptions about the functional form of the production function

These two points are at the core of critiques of SFA and are also a great concern in this work. On the other hand there are also at least two important disadvantages of DEA when compared to SFA:

- DEA doesn't account for noise / measurement error
- it is not possible to conduct conventional tests of hypothesis

Mortimer [2002] conducted a systematic review of DEA and SFA comparisons and finds that neither (and also of other available techniques) is the single best answer to all problems. But still he finds some guidelines: DEA tends to give more accurate results if

- measurement errors and / or statistical noise in the data is only little
- the sample size is very small

Unfortunately we don't really know what a very small sample size is. Resti [2000] who performed the actual research behind this guideline compares the results from two sample sizes: 500 as the 'big' and 50 as the 'small' sample. Using her simulated data she finds that SFA outperforms DEA in the big sample models and is outperformed in the small sample models.

DEA performs worse

- at corner points where only few data points are available
- in regions where the 'true' frontier is non-convex

To sum up: there is not one best method. Both methods can be and are widely used in applied research. In the end it is always important to know about the weaknesses. Knowing these guidelines might give some hints, but still we face the problem that in the real world we still don't really know which technique to choose in our specific data situation. We don't know about measurement errors and statistical noise. We don't know about regions where the production frontier is non-convex. For this reason it seems to be useful to use both techniques and compare the results. A DEA study has already been conducted by the IHS in the year 2008 and in the following we will construct a model analogously to their best estimate and use the same dataset. Finally we compare the results.

3.2.2 Results

Czypionka et al. [2008] estimated many different specifications for their research on Austrian hospital efficiency. They identified one model as their

Table 3.8: Results DEA - SFA I

Model	Mean	Min	Max
DEA VRS	81.35%	49.44%	100.00%
DEA CRS	77.64%	48.04%	100.00%
SFA	87.43%	46.27%	98.94%

best estimate, model '1s'. Model 1s includes LKF points as output and the FTE doctors, FTE other personnel, expenditures on material, and other expenditures as input variables. It was estimated assuming both: constant returns to scale (CRS) and variable returns to scale (VRS). We constructed a similar model using the same data and comparable variables. As we have seen before we have to use input prices rather than quantities for the SFA cost efficiency estimation. So instead of using the number of FTE doctors or other personnel, we used their hospital specific wage rate. To get prices for material and other costs we divided them by the total number of beds. The underlying production function is cobb-douglas and the error-distribution is assumed to be truncated-normal. The one stage estimation technique was employed.

Although the IHS study argues strongly in favor of the VRS model, we are comparing the SFA results also to the CRS results. As a first step it is useful to compare the basic results, that is, the efficiency scores which are derived. We see that the derived efficiency scores are relatively similar with mean inefficiencies of between 12.6% and 22.4%. The correlation of the efficiency scores reveals more. The two DEA models are highly correlated showing a Pearson correlation of 0.9. If we compare the SFA with the two different DEA models it is relatively clear that the CRS version is much closer to the SFA results than the VRS one. A closer look at the efficiency scores derived from the SFA model compared to the VRS model reveals that the very big hospitals are performing much better in the VRS case. A

Table 3.9: Results DEA - SFA II

	DEA VRS	DEA CRS	SFA
DEA VRS	1		
	1		
DEA CRS	0.90	1	
	0.79	1	
SFA	0.57	0.76	1
	0.52	0.66	1

first row: Pearson, second row: Spearman

Table 3.10: Results DEA VRS - SFA III

Range	Number of Hospitals	Mean of Beds	Median of Beds
< -0.15	36	230.6	209.5
-0.15 – 0.00	49	271.5	218
0.00 – 0.15	39	434.8	279
> 0.15	8	1282.1	1189.5

calculation of a VRS model will by definition lead to higher efficiency scores for bigger hospitals than a CRS model. To get a better understanding of this we constructed a new variable which is simply the DEA VRS score minus the SFA score and looked at the differing results comparing the average number of beds. Table 3.10 reveals that there are indeed great differences between the two techniques. The group of hospitals which performed much better in the DEA VRS case was made up completely of very big hospitals. The same table can be made to compare the DEA CRS and the SFA results. This one would show that there is not such a clear pattern visible anymore (please refer to the Appendix if interested in this table). Finally and probably most importantly we will consider the inefficiency explanatory variables and thus second stage DEA results with the one stage SFA results. We re-did the second stage of the DEA, which is simply a regression of some variables on the efficiency scores. But to arrive at comparable results we had to regress the same variables now on the reciprocal value of the efficiencies. This is due to the already mentioned fact that in the one stage SFA the coefficients for the efficiency terms are calculated not on the efficiency scores but on their reciprocal values.

The first thing that one can see is that similar variables are significant according to both techniques. There are only very few coefficients which are significant for the two DEA and insignificant for SFA model or the other way around. Where the coefficients are significant in both cases, the signs also point in the same direction. In general We can conclude that the size of the coefficients are very much comparable. Especially the DEA CRS and the SFA results are in most cases very similar. Similar results across the applied models over groups of hospitals can in this case be seen as an indicator that the results are quite stable and that the two models don't contradict each other. A simplified table of the results is given here in table 3.11. This table only includes variables which are significant at least at the 5% level in both cases. The full results can be found in the appendix.

3.2.3 Conclusion

The findings of this short comparison include:

- CRS DEA calculations are much closer related to SFA results than VRS DEA calculations
- DEA using VRS leads to much higher efficiency scores for very big hospitals
- the results of the inefficiency explanatory variables are very comparable and stable over the three investigated models

Overall it seems to be very useful to calculate efficiency scores using both techniques. Although the agreement over the three models seems to be

Table 3.11: Estimation Results DEA and SFA

	DEA VRS	DEA CRS	SFA
Variable	**Coefficient**	**Coefficient**	**Coefficient**
Congregation	-0.155**	-0.200**	-0.370**
Other	-0.335**	-0.400**	-0.782**
Patient Structure F 40-69	-1.068*	-1.283*	-2.153**
Carinthia	-0.311**	-0.322**	-0.411**
Lower A	-0.334**	-0.420**	-0.459**
Upper A	-0.355**	-0.444**	-0.352**
Salzburg	-0.298**	-0.338**	-0.311*
Styria	-0.229**	-0.294**	-0.256**
Tyrol	-0.421**	-0.514**	-0.699**
Vorarlberg	-0.215*	-0.288**	-0.333**
Intercept	2.504**	2.764**	1.653**

Significance levels : † : 10% $*$: 5% $**$: 1%

very high, we must not forget about the very different results for the biggest hospitals. Further research on this topic would be needed. From our research until now it is not really clear which technique is the one that provides better estimates for this group.

Chapter 4

Final Words

Given the ever growing expenditures on health care in general and hospital care in particular countries of the western world are discussing ways to slow down this development.

Research mainly from the United States has shown that many hospitals are not working efficiently. The applied techniques have in most of the cases been Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). This thesis is the first to apply SFA on Austrian hospital data. The study showed that inefficiencies exist in the Austrian hospital sector. While they may stem from various sources it has especially been shown that ownership and regional differences must play a role. Hospitals run by congregations and other private not for profit owners perform significantly better than state run hospitals. Viennese hospitals are associated with lower efficiency scores than hospitals in all other regions. Especially Carinthia and Tyrol are performing far better. In a second step the results from an earlier DEA study are compared to SFA results to get a better understanding of how the results differ when another technique is applied. It has been shown that a DEA constant returns to scale model returns results which are more similar to the SFA results than a DEA variable returns to scale model. On the level of groups of hospitals (regional or ownership groups) it can be seen that the results are very stable across the two different techniques.

A panel analysis of Austrian hospitals would be a very welcome next step for future research. Unfortunately there are some problems which have to be overcome for this purpose:

- The definition of LKF points changes from time to time
- The time series of available data is still too short (from 2002 onwards) to justify the use of panel analysis

The second point will however change in the coming years and it will be very interesting to see how the efficiencies evolve over time.

While this thesis did a small comparison of DEA and SFA results there is still a lack of reliable literature on this. Finally, it would be good to include real outcome quality indicators in future research. Until now there is simply no data available on this.

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Appendix A

Variable description

Table A.1: Variable Description

	variable	mean	sd	cv	min	max
Inpatient	total expenditures	54,945,257	72,706,580	1.32	2,661,647	540,400,176
	LKF	46,252,023	53,031,205	1.15	2,627,770	325,162,074
	Wage rate	48,346	4,200	0.09	36,205	66,476
	Capital price	16,291	11,220	0.69	1,769	103,583
In- and outpatient	total expenditures	77,458,445	121,774,375	1.57	2,970,280	1,019,308,284
	Number of outpatients	54,075	85,020	1.57	575	612,848
	Wage rate	47,508	3,632	0.08	38,060	63,888

capital price is the same for inpatient only and the whole hospital since it is not possible to differentiate the used capital

sd: standard deviation, cv: coefficient of variation, min: minimum value, max: maximum value

Appendix B

Tables for DEA SFA comparison

Table B.1: Estimation Results DEA VRS

Variable	**Coefficient**	**(Std. Err.)**
Congregation	-0.155**	(0.046)
Confession	-0.243*	(0.101)
Municipality	-0.124*	(0.060)
Other	-0.335**	(0.091)
ps_m_4069	0.497	(0.760)
ps_m_70plus	-1.215	(0.804)
ps_f_0040	-0.297	(0.729)
ps_f_4069	-1.068*	(0.481)
ps_f_70plus	0.600	(0.602)
Burgenland	-0.237*	(0.100)
Carinthia	-0.311**	(0.073)
Loweraut	-0.334**	(0.064)
Upperaut	-0.354**	(0.060)
Salzburg	-0.298**	(0.077)
Styria	-0.229**	(0.061)
Tyrol	-0.421**	(0.078)
Vorarlberg	-0.215*	(0.085)
Central hospital	-0.031	(0.072)
Standard hospital	-0.038	(0.082)
Special hospital	-0.005	(0.094)
Beds	0.000**	(0.000)
Patient days / bed	-0.002**	(0.001)
Intercept	2.504**	(0.459)
R^2	0.506	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

base group: Viennese state run hospitals

Table B.2: Estimation Results DEA CRS

Variable	Coefficient	(Std. Err.)
Congregation	-0.201**	(0.048)
Confession	-0.261*	(0.107)
Municipality	-0.126†	(0.064)
Other	-0.400**	(0.097)
ps_m_4069	0.139	(0.808)
ps_m_70plus	-1.188	(0.854)
ps_f_0040	-0.633	(0.774)
ps_f_4069	-1.283*	(0.510)
ps_f_70plus	0.554	(0.639)
Burgenland	-0.307**	(0.106)
Carinthia	-0.322**	(0.077)
Loweraut	-0.420**	(0.068)
Upperaut	-0.444**	(0.063)
Salzburg	-0.338**	(0.082)
Styria	-0.294**	(0.065)
Tyrol	-0.514**	(0.083)
Vorarlberg	-0.288**	(0.090)
Central hospital	-0.057	(0.076)
Standard hospital	-0.079	(0.088)
Special hospital	-0.031	(0.099)
Beds	0.000	(0.000)
Patient days / bed	-0.002**	(0.001)
Intercept	2.764**	(0.488)
R^2	0.546	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

base group: Viennese state run hospitals

Table B.3: Estimation Results SFA

Variable	Coefficient	SE.
LKF	0.922**	(0.024)
Wage rate other	0.871**	(0.119)
Material cost	0.047	(0.039)
Other cost	0.165**	(0.048)
Intercept	-9.256**	(0.426)
Congregation	-0.370**	(0.074)
Confession	-0.732	(0.438)
Municipality	-0.224	(0.116)
Other	-0.782**	(0.123)
ps_m_4069	0.574	(0.770)
ps_m_70plus	-3.013**	(1.145)
ps_f_0040	-0.803	(0.622)
ps_f_4069	-2.153**	(0.582)
ps_f_70plus	1.345*	(0.529)
Burgenland	-0.271	(0.139)
Carinthia	-0.411**	(0.141)
Loweraut	-0.459**	(0.116)
Upperaut	-0.352**	(0.07)
Salzburg	-0.311*	(0.124)
Styria	-0.256**	(0.093)
Tyrol	-0.699**	(0.152)
Vorarlberg	-0.333**	(0.119)
Central hospital	-0.041	(0.101)
Standard hospital	-0.111	(0.114)
Special hospital	-0.016	(0.102)
Beds	0.000	(0.000)
Patient days / bed	-0.002	(0.001)
Intercept	1.653**	(0.520)
σ^2	0.019**	(0.005)
γ	0.473**	(0.116)
Log likelihood	**99.912**	

Significance levels : † : 10% $*$: 5% $**$: 1%

base group: Viennese state run hospitals

Table B.4: Comparison DEA CRS - SFA

Range			Number of Hospitals	Mean of Beds	Median of Beds
	<	-0.15	43	231.0	208.0
-0.15	–	0.00	61	423.8	276.0
0.00	–	0.15	27	453.9	247.0
	>	0.15	1	782.0	782.0

Appendix C

Zusammenfassung

Diese Diplomarbeit wendet eine Stochastic Frontier Analysis (SFA) auf Daten der österreichischen Fondsspitäler an. Das Ziel hierbei ist eine Evaluierung der Effizienz des österreichischen Spitalswesen. Es wird gezeigt, dass beträchtliche Effizienzdefizite existieren. Es lassen sich statistisch signifikante Unterschiede zwischen einzelnen Regionen und Eigentümern erkennen. Weiters zeigt ein systematischer Vergleich mit einer Data Envelopment Analysis (DEA) Studie, dass ein DEA Model der 'constant returns to scale' Variante den SFA Ergebnissen wesentlich ähnlicher ist als die Ergebnisse des DEA 'variable returns to scale' Modells. Ingesamt lässt sich jedoch feststellen, dass die Ergebnisse unabhängig von der angewandten Technik gleiche Tendenzen aufzeigen und sich somit gegenseitig bestätigen.

Appendix D

Curriculum Vitae

Contact

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Personal Details

Date of Birth:	22nd December 1983
Nationality:	German

Education

since 2008	Student Assistant at the Institute for Advanced Studies (IHS), Vienna, in the Field of Health Economics
2007–2008	Erasmus Exchange: Université Paris I, Panthéon - Sorbonne.
since 2005	Diploma Studies in Economics, University of Vienna

Scientific Work

2010	Kraus, Czypionka, Riedel, Röhrling, Goltz: Formal and Informal Care in Europe, Presentation, Workshop Rom, ANCIEN Project.
2010	Kraus, Czypionka, Riedel, Röhrling, Goltz: Formal Care in Europe, Research Report, ANCIEN Project, forthcoming.
2010	Kraus, Czypionka, Riedel, Röhrling, Goltz: Informal Care in Europe, Research Report, ANCIEN Project, forthcoming.
2009	Czypionka, Riedel, Röhrling, Goltz: Internationale Datenquellen zu Ausgaben für und Outcome von Kindergesundheit in den OECD-Ländern *('International Data Sources of Expenditures and Outcome of Child Health')*, Report, IHS.
2009	Czypionka, Kraus, Röhrling, Goltz: Demenzversorgung in Europa *('Dementia Care in Europe')*, Health System Watch IV / 2009.

Language Skills

German	Mother Tongue
English	Fluent
French	Intermediate

Computer Skills

MS Office	Good Knowledge
Stata	Good Knowledge
LaTeX	Good Knowledge
EViews	Basic Knowledge
SPSS	Basic Knowledge