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RIGOROUS THESIS

Efficiency of Hospitals in the Czech Republic: DEA & SFA Applications

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Declaration of Authorship

I hereby declare that I compiled this thesis independently, using only the listed resources and literature.

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Prague, February 4, 2011

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Abstract

This rigorous thesis estimates cost efficiency of 99 general hospitals in the Czech Republic during 2001–2008 using the Data Envelopment Analysis (DEA) and the Stochastic Frontier Analysis (SFA). It tests comparability of their results finding out a certain qualitative similarity. Next, determinants were added into SFA and efficiency of Czech hospitals examined. The presence of inefficiency is group specific even having accounted for various determinants. Effects of determinants were tested. Inefficiency increases with teaching status, more than 20,000 treated patients a year, not-for-profit status, larger share of the elderly in the municipality and average salary in the district. Inefficiency decreases with less than 10,000 patients treated a year, larger population, higher unemployment rate and more hospitals in the region. The IES WP enclosed incorporates comments raised previously against the master thesis, i.e. excludes the effect of unemployment as a determinant from the SFA model; it furhter uses wages direcly in the the cost function. Considerable similarity between the two SFA models has been found both in terms of coefficients and signs of the remaining variables, as well as, in terms of resulting efficiency scores. The effect of the labor market is thus dual in the former case but it is accounted for when wages are included directly into the cost function.

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Abstrakt

Rigorózní práce hodnotí efektivitu 99 českých nemocnic v letech 2001–2008 metodou obalu dat (DEA) a stochastickou obálkovou analýzou (SFA). Testuje slučitelnost výsledků z obou metod. Zjišťuje, že obě metody podávají kvalitativně podobné výsledky. Následně jsou do stochastické analýzy zahrnuty determinanty efektivnosti a hodnocena efektivita. Bylo zjištěno že neefektivita je specifická pro skupiny nemocnic i po zahrnutí determinantů. Byly hodnoceny vlivy determinantů. Neefektivita roste pro fakultní nemocnice, s léčením více než 20 000 pacientů ročně, neziskovou formou, podílem osob nad 65 let v obci a průměrnou mzdou v kraji. Neefektivita naopak klesá s méně než 10 000 léčenými pacienty ročně, populací obce, mírou nezaměstnanosti a více nemocnicemi v kraji. Přiložený IES WP zahrnuje komenáře vznesené při obhajobě diplomové práce, tj. nezahrnuje efekt nezaměstnanosti jako determinantu v SFA modelu, dále používá mzdy přímo v nákladové funkci. Mezi oběma SFA modely byla zjištěna značná podobnost nejen v hodnotách a směrech působení zbývajících proměnných, ale i ve výsledných hodnotách efektivity. Působení vlivu trhu práce je tedy duální v prvním měření. V druhém měření je celý tento efekt ošetřen zahrnutím mzdy přímo do funkce.

JEL klasifikace	D24, I11
Klíčová slova	efektivita, nemocnice, ČR, metoda obalu dat, stochastická obálková analýza

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Contents

List of Tables

List of Figures

Acronyms

BCC Banker, Charnes, Cooper, VRS DEA Model

COLS Corrected Ordinary Least Squares

CRS Constant Returns to Scale

DEA Data Envelopment Analysis

DMU Decision-Making Unit

DRG Diagnostic Related Groups

FDH Free Disposable Hull

GGHE General Government Expenditure on Health

MLE Maximum Likelihood Estimation

OECD Organisation for Economic Cooperation and Development

PCA Principal Component Analysis

PPS Purchasing Power Standards

SFA Stochastic Frontier Analysis

VRS Variable Returns to Scale

UZIS Institute of Health Information and Statistics of the Czech Republic

Chapter 1

Introduction

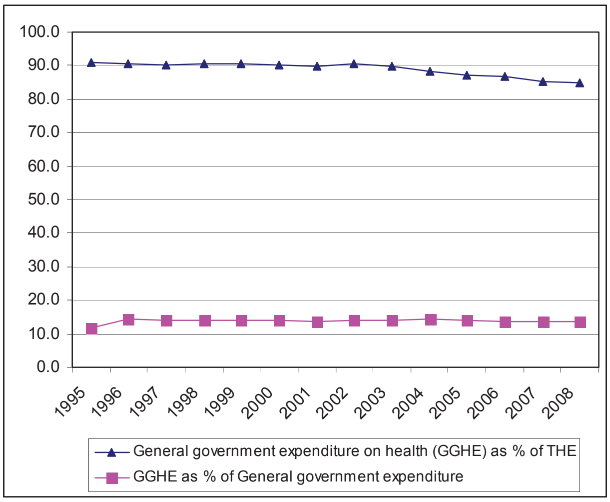
Tightening budget and increasing pressures on the efficiency of public spending represent currently major challenges for the Czech government. Health care provision is not an exception. Public financing of health care in the Czech Republic is still enormous. Out of 250,802 million CZK which was expended on health care in 2008, general government expenditure amounted to 84.7 %. From all OECD countries, only Luxembourg finances a larger share of its health care expenditures publicly (90%)[1]. No wonder there have been pressures on decreasing public funding of health care in the Czech Republic, which is depicted in Figure 1.1. However, it is obvious at the same time that the share of health care expenditure in the total government expenditure has been relatively stable over time, reaching 13 % on average.

Debates about inefficiency of the Czech health care system have resulted in a number of reforms. The major ones include increasing private involvement on health care funding and privatization of hospitals. Even though hospitals have been transformed into joint-stock companies in the view of increasing their efficiency, in many cases regions, districts or municipalities are their major shareholders. There is only about 5 % of hospitals owned by a private entity. With the changing nature of Czech hospitals the question of their efficiency after the reform naturally arises. Indicators of relative efficiency are necessary to gauge whether the cost-containment efforts were successful.

From the international perspective, Greene (2003) estimated efficiency of national health care systems in 191 countries. Unfortunately, there was long a methodological gap in the measurement of efficiency of the hospital sector

[1] http://www.oecdilibrary.org/oecd/content/table/20758480-table3

Figure 1.1: Government Expenditure on Health in the Czech Republic



Source: www.who.int

within countries. The first technique to measure efficiency was developed by Farrell (1957) when searching for ways of evaluating efficiency of for-profit corporations in the U.S.A. Throughout the time, the methodology started to penetrate into the public sector as a means to evaluate efficiency of governments. One of the most widely acknowledged studies includes Schuknecht *et al.* (2003) who measured efficiency of governments in Europe. On a rather local scale De Borger & Kerstens (1996) analyzed efficiency of Belgian municipal governments using different efficiency methods. Education or health care as separate areas of public economics followed shortly thereafter. Health care studies are now to be found worldwide for various types of health care institutions such as nursing homes or hospitals.

The first empirical literature on measuring efficiency of hospitals appeared in 1980s, examples include Nunamaker (1983) or Sherman (1984) who estimated efficiency of a sample of US hospitals. However, their primary purpose was to test the appropriateness of frontier models (specifically the Data Envelopment Analysis at the time) to be used in the sphere of health care.

Since 1990s measuring efficiency of hospitals as well as examining its determinants has been a major interest of health care economics all around the world. A number of studies analyzed US data, such as Zuckerman *et al.* (1994), Rosko & Chilingerian (1999), Vitaliano & Toren (1996), Wang *et al.* (1999) or Rosko (2001). However, studies measuring hospital efficiency in Europe were not rare either in 1990s. Wagstaff & Lopez (1996) and Prior (1996) analyzed efficiency of Spanish hospitals, Parkin & Hollingsworth (1997) studied hospitals in Scotland, Linna & Häkkinen (1998) dealt with efficiency of Finnish hospitals. Magnussen (1996) analyzed Norwegian hospitals.

With the year 2000 the number of countries analyzing efficiency of their hospital sector increased remarkably. These include analysis of German hospitals which appears in Staat (2006), Frohloff (2007) or Herr (2008), Austrian hospitals as in Hofmarcher *et al.* (2002), hospitals in Greece in Maniadakis & Thanassoulis (2004) or Kontodimopoulos *et al.* (2006). Swiss hospitals were studies in Farsi & Filippini (2004). Jacobs (2001) analyzed hospitals in the United Kingdom and Afonso & Fernandes (2008) did alike for hospitals in Portugal. Mortimer *et al.* (2002) estimated efficiency of hospitals in Victoria, Australia. The list is however not exhaustive, more examples can be found in Worthington (2004) or Hollingsworth (2008) who provide an overview of empirical studies dealing with hospital efficiency measurement, the latter of which is updated on a regular basis.

Individual efficiency scores are dependent on the characteristic features of each unit examined. When not accounted for, lower efficiency scores are taken as inefficiency even though caused by the environmental factors. Therefore, determinants of inefficiency are examined in most of the studies as well, however exceptions appear. Depending on the purpose of the study and environmental circumstances, various determinants are included. Zuckerman *et al.* (1994) is considered to be a pioneering work in the examination of determinants of inefficiency. They analyzed the effects of ownership type, location and teaching status on cost efficiency of a sample of US hospitals.

The effect of ownership status on inefficiency has been empirically widely examined. Besides Zuckerman *et al.* (1994), also Rosko & Chilingerian (1999), Rosko (2001) or Folland & Hofler (2001) dealt with this effect and consistently found out that government regulatory pressures are inversely associated with inefficiency. On the other hand Vitaliano & Toren (1996) found the effect of both for-profit status and government ownership on inefficiency to be insignificant.

The effect of competition and inefficiency have been found to be inverse-related, however, insignificant by some studies, such as Zuckerman *et al.* (1994) or Cellini *et al.* (2000), the latter of which analyzed the effect of competition on efficiency of hospitals in Italy. Rosko & Chilingerian (1999) and Rosko (2001), on the other hand, found this effect to be significant.

As far as hospital size is concerned, the evidence is rather mixed. It has been found that larger hospitals are different from smaller ones. Zuckerman *et al.* (1994) found out that size, as measured with the number of beds, is significantly and negatively related to inefficiency when regressing obtained inefficiency results on a set of determinants. The same conclusion was reached by Vitaliano & Toren (1996), specifically, when including size variable into the regression, they found that having up to 120 beds is positively related to inefficiency, but when there are more than 300 beds, the effect on inefficiency is negative. Similarly, Wang *et al.* (1999) who measured a different sample of US hospitals, found out that large hospitals generally demonstrate higher inefficiency when the size effect is not accounted for. On the other hand, using log of available beds to account for size, Yong & Harris (1999) found out that size is positively related to inefficiency.

The high number of empirical studies dealing with hospital efficiency and its determinants abroad supports the necessity to deal with the subject matter. Unfortunately, a similar analysis of hospital efficiency is scarce or even missing in former Communist countries including the Czech Republic. An analysis of efficiency of hospitals in the Czech Republic has been carried out only in Dlouhý *et al.* (2007) so far. They estimated technical efficiency of a cross-sectional sample of 22 Czech hospitals in 2003. Not only was the sample size quite small, but no effect of environmental factors on inefficiency was taken into account. It is believed that an extensive analysis of efficiency of Czech hospitals as well as the effects of environmental factors need to supplement Dlouhý *et al.* (2007) so that the Czech Republic has an analysis of hospitals comparable to those available abroad. This thesis thus aims to contribute to this field of research.

Two techniques to estimate efficiency of Czech hospitals are used in this thesis. The Data Envelopment Analysis as a non-parametric programming method; and the Stochastic Frontier Analysis which is a parametric method that introduces statistical noise into the model. The methods are based on different assumptions and requirements, therefore, quantitative results obtained from each of them are likely to differ. But their purpose is the same - to envelop the data such that the level of inefficiency of individual units is revealed. They have thus often been used as complementary tools. In the latter stages of the analysis, various determinants of inefficiency are added to the SFA regression and an additional technique thus employed.

Using data envelopment techniques, this thesis tries to answer the following questions:

1. How efficient are Czech hospitals under DEA and SFA without determinants? How do efficiency scores differ when various envelopment methods are used? Are DEA and SFA (without determinants) indeed complementary tools?

2. Having added determinants of inefficiency into the SFA analysis, what is the size, mean and variance of inefficiency of Czech hospitals?

3. Which exogenous environmental factors, such as hospital status or geographical setting, influence the estimated inefficiency scores? What effect do they have?

4. How much do individual efficiencies differ in the SFA in terms of ranking with and without determinants?

The thesis analyzes 99 Czech hospitals in the period 2001-2008, the data on which is regularly collected by The Institute of Health Information and Statistics. Only general hospitals were subject of the analysis, specialized clinics and separate nursing homes were excluded. Total inpatient cost adjusted for inflation is used as the only input variable. Inpatient days, doctor/bed and nurse/bed ratios are used as output variables. A means to account for severity of cases in inpatient days was developed. An additional DEA analysis for 2004 cross-section was carried out to uncover the effect of technology on inefficiency. Including technology indices into the overall analysis was, however, hampered by the data availability for the remaining years.

Data on the determinants of inefficiency were obtained from The Institute of Health Information and Statistics, The Czech Statistical Office and The Registry of Companies of the Czech Republic. The man part of the thesis analyzes the effect of nine determinants of inefficiency - teaching status, size of up to 10,000 patients treated a year, size of more than 20,000 patients treated a year, not-for-profit status, size of the population, share of the elderly in the population, unemployment rate in the districts of municipalities with extended powers, average salary and the number of hospitals in the region. All determinants proved to have a significant effect on inefficiency.

The IES Working Paper, which is enclosed in the appendix, is based on the parametric estimation in the main analysis of this thesis and addresses comments raised previously.[2] It thus excludes the effect of unemployment as a determinant of inefficiency. It furthermore includes average salary into the stochastic frontier cost function. Considerable similarity has been found between the two SFA models, both in terms of coefficients and signs of the remaining variables, as well as, in terms of the resulting efficiency scores. The effect of the labor market is thus dual in the former case but it is accounted for with similar results when wages are included directly into the cost function.

This rigorous thesis is organized as follows. Chapter 2 summarizes the estimation methodology explaining the substance of the Data Envelopment Analysis and the Stochastic Frontier Analysis as tools to measure efficiency. Chapter 3 presents the dataset and introduces variables employed. Hypotheses on the effects of the determinants on inefficiency are expresses. Chapter 4 deals with a preliminary analysis of the data in order to identify potential ills and corrects for them. Chapter 5 presents results of the efficiency estimation using the Data Envelopment Analysis, the Stochastic Frontier Analysis and the Stochastic Frontier Analysis with Determinants. Efficiency scores and rankings obtained from different methods are discussed and compared. At the same time, effects of different environmental factors are analyzed. Consequently, efficiency scores for individual hospitals are thoroughly analyzed an commented upon. Chapter 6 relates the results obtained in the parametric part of this thesis and the IES Working paper which is enclosed in the appendix. Chapter 7 concludes and provides motivation for further research.

[2] The main part of this Rigorous Thesis was defended with honor as a Master Thesis called "Measuring Efficiency of Hospitals in the Czech Republic"

Chapter 2

Methodology

In most economic activities inputs are transformed into outputs. Measuring efficiency of this process thus naturally comes into play. Generally speaking, the purpose of efficiency measurement is to find the maximum feasible amount of output which can be obtained from a given set of input. A number of techniques to estimate efficiency have been developed over past 40 years. The most widely applied approaches are frontier techniques. These determine the distance of an individual observation from the efficiency frontier. Such a frontier is formed from fully efficient observations from the data set, i.e. those which employ inputs utmost economically.

The pioneering work on efficiency methods of Farrell (1957) dealt with **technical efficiency**. Such a method employs inputs and outputs in physical units without the requirement on any price information. It states that if an organization is technically efficient, it is placed on the frontier. Farrell's concept was enriched by Charnes *et al.* (1978) who introduced the concept of **allocative efficiency** stating that even if an observation is placed on the frontier (from Farrell's perspective), allocative inefficiency is present if it uses a mix of inputs in suboptimal proportions given their respective prices and available technology. Measuring allocative efficiency is thus more demanding on data availability since price information is required. Technical and allocative efficiently together represent the overall **economic efficiency**. In this thesis, total costs will be used as the only input variable which is transformed into various outputs, thus cost efficiency will be analyzed.

Depending on the purpose of the study, efficiency can be measured as input or output-oriented. In the **input orientation**, under a given level of output, observations are compared in terms of input minimization, while in the **output orientation**, input is given but output maximized. In other words, if an observation, a Decision Making Unit (further 'DMU') as called in the frontier literature, is placed on the frontier, it produces the same amount of output employing less input than other DMUs below the frontier or, alternatively, it produces more output for a given level of input. Whether input or output orientation is selected depends to a large extent on what managers of the particular set of DMUs have most control over (Coelli 1996a, p. 23). A majority of studies in the health care sector have applied input-oriented models since the DMUs have usually a certain level of output exogenously set, for they respond to the demands from the community (Zuckerman *et al.* 1994; Yong & Harris 1999; Vitaliano & Toren 1996; Kontodimopoulos *et al.* 2006). This thesis will thus measure the input oriented cost efficiency.

Primary division of frontier techniques is into parametric and non-parametric; deterministic and stochastic approaches.
Parametric methods, aim at determining efficiency of an organization against some idealized benchmark, while **non-parametric methods** evaluate efficiency of an organization relative to other DMUs in the set. The parametric method requires that the cost function be specified in order for the efficiency frontier to be formed. There is no such requirement in non-parametric methods. These instead employ data in natural units.

Deterministic and stochastic approaches differ in the attitude to the error term. **Deterministic methods** assume that the entire deviation from the frontier is caused by inefficiency. On the contrary, **stochastic approaches** acknowledge that the deviation from the frontier is composed of two parts, one representing inefficiency and the other randomness. That is to say, the stochastic frontier approach acknowledges external factors which may include differences in uncontrollables directly connected with the production function, i.e. operating environments; or econometric errors, i.e. misspecification of the production function and measurement errors. It implies therefore that when using a deterministic approach, no observation can lie above the efficient set, however, this must not necessarily be the case with the stochastic approach since randomness can shift the DMU concerned above or below the efficiency frontier.

Table 2.1 provides an overview of basic methods encountered in the literature with some frequency. As suggested above, under Stochastic Frontier Analysis (further 'SFA'), an idealized benchmark is assumed to be known and the deviation is composed of inefficiency and a random element. Corrected Ordinary Least Squares (further 'COLS') is a frontier variant of Ordinary Least Squares ('OLS'), i.e. the estimated line does not lie among the observations but envelops them from above. The entire error term ϵ is interpreted as inefficiency. In case of Data Envelopment Analysis (further 'DEA') and Free Disposable Hull (further 'FDH'), the frontier is constructed from the data in natural terms. However, DEA is more restrictive of the two due to convexity assumptions.

Table 2.1: Overview of Frontier Methods

	Parametric	Non-parametric
Stochastic	Stochastic Frontier Analysis SFA	
Deterministic	Corrected Ordinary Least Squares COLS	Data Envelopment Analysis DEA Free Disposable Hull FDH

Since DEA as a non-parametric approach and SFA as a parametric approach were found most often to be employed in the health care literature, they will be applied for the analysis in this thesis. Furthermore, it has been argued that parametric and non-parametric methods should be used as complementary tools when possible. It is pointed out by Chirikos & Sear (2000) and Kooreman (1994a) that efficiency scores obtained from each method at the individual level differ, which could be attributed to the difference in attitude to random shock. But rankings obtained from the two methods were found to some extent correlated. The methods thus reinforce each other. (For more discussion see also Hollingsworth (2008) and Valdmanis (1992)).

The following sections aim to explain the theoretical underpinnings behind the Data Envelopment Analysis and the Stochastic Frontier Analysis. They will concentrate primarily on the concepts applied in this thesis, even though the chapter will also marginally outline further, otherwise relevant, ideas.

2.1 Data Envelopment Analysis

The Data Envelopment Analysis (further 'DEA') as an approach to measure efficiency was first proposed by Farrell (1957) when seeking for better ways of productivity evaluations. In his work, Farrell also divided concepts of productivity and efficiency. Farrell's concepts were later developed into a practical research tool used in various areas of economic research by Charnes *et al.* (1978).

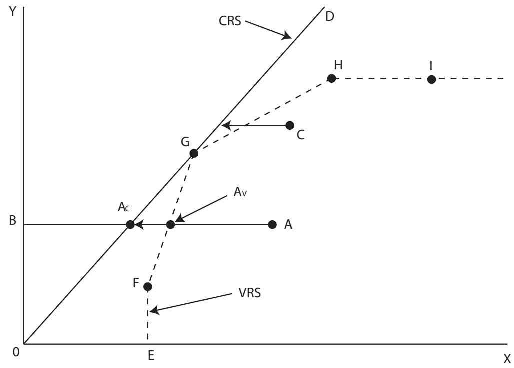
DEA has numerous advantages, particularly for public sector applications, the major of which is that it can accommodate multiple units of input and output without the need for any kind of aggregation. This makes it highly appropriate to be applied in sectors where price information is not available or unreliable, such as health care (Hollingsworth & Peacock 2008; Valdmanis 1992). Furthermore, DEA is driven by the assumption that the production function is not directly observable, thus no specification of a functional form is needed. Instead, the locus of fully efficient organizations must be obtained from the observed input and output data. There is nevertheless, one important assumption which DEA must fulfill, namely the convexity assumption.[1]

Efficiency estimation using DEA proceeds in two steps. Firstly, the efficiency frontier is computed. At this point a decision on either constant or variable returns to scale has to be made. Consequently, inefficient DMUs lying below the frontier are compared to it. In Figure 2.1 such a referent frontier is depicted, depending on the assumption of the scale of production, by either the Constant Returns to Scale (further 'CRS') or Variable Returns to Scale (further 'VRS') frontier. For simplicity, the graphical representation includes only One–Input - One–Output space. In reality, however, such a representation is rather tricky due to multidimensionality of inputs and outputs. In Figure 2.1 inefficient DMUs are compared to their respective efficient counterparts and their efficiency levels are obtained. To provide an example, the efficiency level for observation A, is determined as BA_c/BA or BA_v/BA.[2]

[1]Convexity assumption makes DEA distinctive of FDH which envelopes the data more tightly and is thus less restrictive.

[2]A controversial issue is the treatment of slacks, i.e. observations lying on the efficient frontier, however, either on its vertical or horizontal part (such as point I under VRS in Figure 2.1). Such DMUs are efficient by Farrell's definition, which is nevertheless not in accordance with Koopmans (1951), whose interpretation of an efficient DMU is much stricter acknowledging only DMUs with zero slacks as efficient. The treatment of slacks was first outlined by Ali & Seiford (1993). As a consequence of the controversy on the subject, in much of the literature, slacks are completely ignored.

Figure 2.1: Data Envelopment Analysis



Source: based on Coelli *et al.* (2005, p. 174), own graphics

As outlined above, it is important to keep in mind that not necessarily all DMUs operate at an optimal scale. If this is the case the variable returns to scale alternative of this model has to be considered, since otherwise the obtained efficiency values are confounded by the scale efficiency effects; the smaller the sample size, the larger the scale effect as explained by Smith (1997). In case of hospitals, suboptimal scale is often caused by imperfect competition, constraints on finance, regulatory constraints on entry, mergers and exits as noted by Jacobs *et al.* (2006, p. 101).

It is obvious from Figure 2.1 that the VRS convex hull envelops the data more tightly than the CRS frontier. That is, if a production process exhibits a VRS technology, a point on the CRS frontier is unobtainable for some level of production. Under VRS, inefficient DMUs are compared only to DMUs of a similar size, which represents its enormous advantage over CRS. As a result observations F and H become newly efficient under VRS. It is expected that F and H employ a better practice technology. However, as noted by Parkin & Hollingsworth (1997), CRS and VRS are pure assumptions in DEA. In other words, if wrong, VRS only imposes too weak assumptions on the technology underlying the production function.

2.1.1 Formulation

Assume that a DMU produces s different outputs, $\mathbf{y} = (y_1, \ldots, y_s)$ using m different inputs $\mathbf{x} = (x_1, \ldots, x_m)$ and that there is a set of n DMUs, $N = (1, \ldots, n)$. Consequently, the i-th DMU, $i \in N$, is expressed in terms of its input and output vectors such that $DMU_i = (\mathbf{x}_i, \mathbf{y}_i)$ where $\mathbf{x}_i = (x_{1i}, \ldots, x_{mi})$,

$\mathbf{y}_i = (y_{1i}, \ldots, y_{si})$.

The relative efficiency of DMU_i can be obtained by solving the *fractional program* as proposed by Charnes *et al.* (1978, p. 430):

$$\max_{\mathbf{u}_i, \mathbf{v}_i} \frac{\mathbf{u}_i' \mathbf{y}_i}{\mathbf{v}_i' \mathbf{x}_i} \tag{2.1}$$

s.t.:

$$\frac{\mathbf{u}_i' \mathbf{y}_j}{\mathbf{v}_i' \mathbf{x}_j} \leq 1 \quad \text{for} \quad \forall j \in N$$

$$\mathbf{u}_i, \mathbf{v}_i \geq 0$$

where $\mathbf{u}_i$, $\mathbf{v}_i$ are vectors of weights attached to vectors of outputs $\mathbf{y}_i$ and inputs $\mathbf{x}_i$ respectively.

In other words, the mathematical program aims to find the set of input and output weights that maximizes efficiency of the DMU under scrutiny (DMU_i) to cast it in the best possible light subject to the constraint that when these weights are applied to each DMU in the dataset, none has efficiency greater than 1. The linear program must be conducted n times, once for each DMU.

Such a formulation results in an infinite number of solutions. If $(\mathbf{u}_i^*, \mathbf{v}_i^*)$ is a solution of the maximization problem, then also $(\alpha\mathbf{u}_i^*, \alpha\mathbf{v}_i^*)$ are equivalent solutions. An additional constraint thus has to be imposed on either the numerator or the denominator of the efficiency ratio such that it is equal to 1, i.e. $\mathbf{v}_i' \mathbf{x}_i = 1$, to correct for it, as suggested by Charnes *et al.* (1978). Doing so, the fractional form is thus transformed into a *multiplier form.*

Maximization and minimization are dual problems, therefore, the multiplier form equation can be rewritten into the *envelopment form*, i.e. the minimization problem. The advantage of the latter stems primarily from the fact that it involves fewer constraints, and as a result, it is more widely utilized than the two previous forms. Specifically, the previous equation involves $n+m$ parameters to estimate while this one estimates only $n+1$ (Charnes *et al.* 1978; Hollingsworth & Peacock 2008).

$$\min_{\lambda_i,\theta_i} \theta_i \tag{2.2}$$

s.t.:

$$\begin{aligned} &\lambda_i' \mathbf{y}_j \geq \mathbf{y}_i && \forall j \in N \\ &\lambda_i' \mathbf{x}_j - \theta_i \mathbf{x}_i \leq 0 && \forall j \in N \\ &\theta_i, \lambda_i \geq 0 \end{aligned}$$

where λ_i represents a vector of weights attached to each DMU_j in the comparison group from the perspective of DMU_i (Charnes *et al.* 1978). θ_i is relative efficiency of the DMU_i. It results that $\theta_i = 1$ indicates the frontier point and hence that the DMU_i is technically efficient. When $\theta_i < 1$ inefficiency for the DMU_i is present.

In other words, the problem aims to decrease the input vector $\mathbf{x}_i$ as much as possible while still remaining within the feasible input set. The contraction of the input vector $\mathbf{x}_i$ projects an efficient point on the frontier. This projected point is an linear combination of the remaining observed data points. The projected point must fulfill the two above stated constraints. Specifically, the first constraint establishes the weighted linear combination of DMUs which produce at least as much output as the DMU_i. The second constraint requires that the weighted linear combination of other DMUs use no more than a fraction of the m inputs of the DMU_i examined. Since this thesis employs total costs as the only input to production, the input vector will be $n \times 1$. (For comparison see for example Linna *et al.* (2006, p. 273)). Similar to the fractional problem, running n linear problems is needed. The value of θ_i and λ_i vector are thus specific for each DMU.

To account for variable returns to scale an additional constraint for the model has to be introduced.

$$\sum_{j=1}^{n} \lambda_{ij} = 1 \quad \text{for} \quad \forall j \in N \tag{2.3}$$

Such a formulation of the model is often referred to as the BCC model in honor of its proponents Banker *et al.* (1984).

As suggested earlier, DEA has numerous advantages, however, its limitations must be kept in mind as well, particularly when interpreting the results. The limitations are to a greater extent summarized in Hollingsworth & Peacock (2008, p. 37) The major limitations include:

- DEA in itself cannot extensively account for measurement errors or outliers. If such an error occurs and stays undetected, two possible outcomes may result:
  - small error occurring for an inefficient hospital affects the magnitude of the inefficiency estimate only for that hospital;
  - larger random variation or a small variation affecting a frontier DMU moves the entire frontier, which influences the estimates of all other hospitals. It thus has severe consequences for the analysis.

  A few methods to detect outliers have been proposed. However, since they evaluate the dataset from various perspectives, they tend to classify different observations as outliers. It is therefore advisable to use more than one method. (Fried *et al.* 2008, p. 497). This thesis thus employs two different methods to detect outliers in DEA. One of them was proposed by Wilson (1993), the other was developed by Simar (2003). Both of these are explained in Chapter 4 where preliminary analysis of the data is carried out.

- DEA is sensitive to the number of input and output variables with respect to the number of DMUs used in the analysis. Efficiency scores are likely to be overestimated if the number of observation is small. Hollingsworth & Peacock (2008, p. 37) note that "the number of observations should be at least three times the number of input and output variables combined".[3] However, empirical literature employs fewest variables possible in order for them to avoid the possible bias.

- DEA is also sensitive to the inclusion of input and output variables. In other words, no test for the goodness of fit exists.

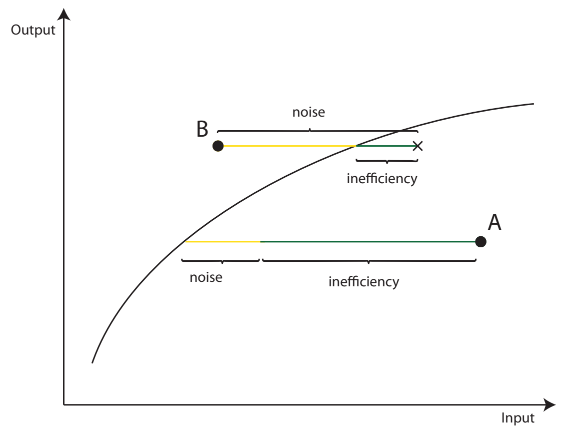
[3] Also noted in Smith (1997).

2.2 Stochastic Frontier Analysis

The Stochastic Frontier Analysis (further 'SFA'), also called the 'Composed Error Model', is a benchmarking parametric technique to estimate efficiency. Its cross–sectional variant was first proposed by Aigner *et al.* (1977) and Meeusen & van den Broeck (1977) independent of each other. The primary advantage over the DEA is the fact that the SFA decomposes the residual, i.e. the deviation from the production frontier, into inefficiency and a random component. It thus addresses the drawbacks of the DEA, particularly the problem of inflating inefficiency for outliers and errors.

This decomposition in one One-Input - One-Output space is depicted in Figure 2.2. It is also obvious that the random part of the deviation from the frontier can shift observations above it, such as point B in Figure 2.2, phenomenon which is impossible in the DEA and other non-stochastic techniques in general.

Figure 2.2: Stochastic Frontier Analysis



However, contrary to DEA, SFA cannot accommodate multiple inputs (in case of input orientation) and thus inputs have to be aggregated into a single variable. It is generally a considerable disadvantage since aggregation might loose some information in the data. Nevertheless, since this thesis employs only a single input to produce multiple outputs, DEA represents no such advantage here.

Further disadvantages include the fact that SFA assumes that the production function of the fully efficient DMUs is known. Initially, SFA dealt only with production functions. Since production and cost functions are dual to each other, maximization or minimization of the function depends only on the purpose of the study. Cost function is more convenient to be used in health care applications and thus such a specification was often encountered in the literature. Cost function will also be considered for the purposes of this thesis. Similar to the DEA, the inefficiency term obtained using the SFA will reveal how far below the cost frontier the DMU concerned operates. The most widely applied functional specifications are Cobb-Douglas and Translog functions.

2.2.1 Formulation

The original cross-sectional version of SFA takes the following form (Aigner *et al.* 1977):

$$y_i = f(\mathbf{x}_i; \beta) + \epsilon_i \tag{2.4}$$

$$\epsilon_i = v_i - u_i$$

where $i \in N$; $N = (1, \dots n)$; y_i is output of DMU_i obtained from the input vector $\mathbf{x}_i$; β is vector of unknown parameters to be estimated; v_i is a random variable assumed to be i.i.d., $v_i \sim N(0, \sigma_v^2)$; u_i represents inefficiency, which is independent of v_i, assumed to be i.i.d., $u_i \sim N^+(0, \sigma_u^2)$. In other words, it is truncated at 0.[4] It is worth emphasizing that when a cost function is estimated, the sign with the inefficiency term changes to $\epsilon_i = v_i + u_i$.

Before formulating the panel data version of the SFA, it is necessary to decide on the specification of the cost function. However, it is to a large extent arbitrary. Majority of the empirical studies discussed used either the Translog function or Cobb-Douglas specification. Table 3.2 at the end of this chapter provides an overview of the specifications used in the empirical literature.

[4]Even though normal-half-normal and truncated-normal are most widely applied assumption on the distribution of the inefficiency term, other assumptions can be made, such as normal-exponential or normal-gamma distribution. Further discussion is provided in Fried *et al.* (2008), chapter 2

Translog function takes the following form:

$$\ln y = \beta_0 + \sum_{q=1}^{S} \beta_q \ln x_q + \frac{1}{2}\sum_{q=1}^{S}\sum_{p=1}^{S} \beta_{qp} \ln x_q \ln x_p \tag{2.5}$$

Cobb-Douglas Function takes the form:

$$\ln y = \beta_0 + \sum_{q=1}^{S} \beta_q \ln x_q \tag{2.6}$$

where $p, q \in S$, in other words, p, q, correspond to different output variables and y corresponds to total costs.

Comparing Cobb-Douglas and Translog specifications, Chirikos & Sear (2000) pointed out that when cross products are included in the Translog Function the mean efficiency score increases due to increased flexibility of the function. On the other hand, Vitaliano & Toren (1996) as well as Chirikos & Sear (2000) in the end preferred Cobb-Douglas since the Translog model causes an extensive loss of the degrees of freedom due to its cross product terms. For Chirikos & Sear (2000) the loss of the degrees of freedom problem overweighted the benefits obtained from the Translog model. Since the model adequacy can only be determined afterwards conducting a residual analysis, hypothesis testing, measuring the goodness-of-fit and assessing predictive performance (Coelli 1996b), for the purposes of this thesis, both Translog and the Cobb-Douglas specification were initially considered. However, based on the results Cobb-Douglas specification proved better. The discussion is provided in Chapter 5, Section 5.1.

Having decided upon the specification of the cost function, the cross-sectional version of Aigner *et al.* (1977) and Meeusen & van den Broeck (1977) can, without major difficulties, be extended to a panel data form (Coelli *et al.* 2005; Greene 2002). Two models will be used to analyze hospitals in the Czech Republic.[5] Firstly, when only output and input data will be analyzed without accounting for heterogeneity, the panel data version of the cost function will take the following form (Battese & Coelli 1992):

$$y_{it} = f(\mathbf{x}_{it}; \beta) + v_{it} + u_{it} \tag{2.7}$$

where $t \in T$; y_{it} is total costs of DMU_i at time t; $\mathbf{x}_{it}$ is a $k \times 1$ vector of outputs of DMU_i at time t; and β is a vector of unknown parameters to be

[5]They are not special cases of each other, rather, they are two different models used for different purposes.

estimated. v_{it} is a random variable which is assumed to be i.i.d., $v_{it} \sim N(0, \sigma_v^2)$ and independent of u_{it}. The technical inefficiency effect u_{it} is expressed as

$$u_{it} = u_i \exp(-\eta(t - T) \tag{2.8}$$

where u_i are non-negative random variables assumed to be independent identically distributed as truncation at zero of the $u_i \sim N(\mu, \sigma_u^2)$ distribution; parameter η allows for time–varying inefficiency and represents a parameter to be estimated.

It is worth pointing out that the period taken into account in the analysis of Czech hospitals is considerably long and, furthermore, many of the hospitals scrutinized changed their legal form or ownership at some point during the period 2001-2008. Therefore, allowing for time–varying inefficiency term is deemed appropriate.

Secondly, the thesis will take advantage of the model developed by Battese & Coelli (1995). It is primarily useful when efficiency determinants are analyzed since this model can accommodate determinants of inefficiency directly in one-step estimation.[6] (Battese & Coelli 1995). The model looks as in 2.7, except, the inefficiency effect is specified as:

$$u_{it} = \delta \mathbf{z}_{it} + w_{it} \tag{2.9}$$

where w_{it} is a random variable defined by truncation of the normal distribution with zero mean and variance, σ^2, such that the truncation point is $-\delta \mathbf{z}_{it}$, i.e. $w_{it} \geq -\delta \mathbf{z}_{it}$. u_{it} is thus of non-negative truncation of the $N(\delta \mathbf{z}_{it}, \sigma^2)$ distribution. In other words, the non-zero mean of the truncated normal distribution of the inefficiency term is:

$$\mu_{it} = \delta \mathbf{z}_{it} \tag{2.10}$$

[6] There are a number of other methods to account for heterogeneity. The simplest possibility includes dividing the sample according to the criterion of interest as in Zuckerman *et al.* (1994), Nayar & Ozcan (2008) or Hofmarcher *et al.* (2002). However, efficiency scores cannot be compared across groups since each sample set has a different reference point. Furthermore, if the sample size is small the analysis is jeopardized. The second possibility comprises a two-stage approach, where efficiency scores from the first stage are regressed on a set of possible determinants, nevertheless, the possibility of bias due to 'left out variables' arises as an immediate objection. As Greene (2003) puts it "if such covariates do have explanatory power, then they should appear in the model at the first step". Moreover, the distributional assumptions used in the first and second steps contradict each other as explained by Coelli *et al.* (2005).

where $\mathbf{z}_{it}$ is a $1 \times p$ vector of potential determinants of efficiency of DMU_i at time t and δ is a vector of parameters to be estimated. In other words, determinants of efficiency influence the mean of the truncated normal distribution. It results, that if all the elements of the δ-vector are equal to zero, technical inefficiency effects are not related to the z-variables and a half-normal distribution (with zero mean) is obtained.

Since the above formulated SFA models will be estimated using maximum likelihood, a parametrization similar to Battese & Corra (1977) will become useful. It creates a joint density function for both inefficiency and the random noise and replaces σ_v^2 and σ_u^2 with

$$\sigma^2 = \sigma_v^2 + \sigma_u^2. \tag{2.11}$$

At the same time parameter γ is identified such that $\gamma = \frac{\sigma_u^2}{(\sigma_v^2+\sigma_u^2)}$

Basically, SFA estimation of inefficiency in a panel relies upon the unobservable u_{it} being predicted. It is obtained as a conditional expectation of u_{it} upon the observed value. In other words, using maximum likelihood[7], only

$$\epsilon_{it} = v_{it} + u_{it} = y_{it} - \beta x_{it} \tag{2.12}$$

can be directly observed. Consequently, time and DMU specific inefficiency u_{it} is conditioned upon the observed overall residual as in Jondrow *et al.* (1982) or Battese & Coelli (1988):[8]

$$E[u_{it}|\epsilon_{it}] = \frac{\sigma\lambda}{1+\lambda^2}\Big[\frac{\phi(a_{it})}{1-\Phi(a_{it})} - a_{it}\Big] \tag{2.13}$$

where $\sigma = [\sigma_v^2 + \sigma_u^2]^{\frac{1}{2}}$; $\lambda = \frac{\sigma_u}{\sigma_v}$; $a_{it} = \pm\frac{\epsilon_{it}\lambda}{\sigma}$; $\phi(a_{it})$ is the standard normal density evaluated at a_{it}; $\Phi(a_{it})$ is the standard normal cumulative distribution function evaluated at a_{it}.

To conclude, it is obvious that both DEA and SFA reveal advantages but also shortcomings. Estimating efficiency with one method is thus considered insufficient here. Even though they do not show identical results, it is believed that since both DEA and SFA envelope the data under the rationale of showing

[7]Subject to some sign changes, the log likelihood function of the cost function is to be found in Battese & Coelli (1992).

[8]Jondrow *et al.*'s and Battese & Coelli's definition was tailored to panel data specification similar to Greene (2002).

the most efficient DMUs, outputs from both methods will enrich each other. The reasoning of this thesis to use both methods is backed up by the review of peer studies which sometimes also used both SFA and DEA. Table 2.2 summarizes survey of the literature. Studies are categorized according to the method employed, i.e. DEA or SFA. DEA papers are further subdivided according to whether CRS or VRS were used. SFA is subdivided according to which of the two above described functional specifications was employed. Studies comparing results obtained from DEA and SFA, such as Chirikos & Sear (2000), are duplicated in the Table 2.2. The review is however not exhaustive. A more thorough survey is to be found in Worthington (2004) and Hollingsworth (2008), the later of which is updated on a regular basis.

Table 2.2: Application of Frontier Methods in the Literature

	DEA	
CRS	VRS	Both
Janlov (2007) Afonso & Fernandes (2008) Kontodimopoulos *et al.* (2006) Nayar & Ozcan (2008) Jacobs (2001)[a]	Hofmarcher *et al.* (2002) Linna *et al.* (2006) Valdmanis (1992) Magnussen (1996) Mortimer *et al.* (2002) Staat (2006)	Dlouhý *et al.* (2007) Kooreman (1994a) Prior (1996) Chirikos & Sear (2000) Cellini *et al.* (2000) Parkin & Hollingsworth (1997) Blank & Valdmanis (2005)
	SFA	
Cobb-Douglas	Translog	Both
Farsi & Filippini (2004) Yong & Harris (1999) Vitaliano & Toren (1996) Frohloff (2007) Mortimer *et al.* (2002)	Rosko & Chilingerian (1999) Zuckerman *et al.* (1994) Rosko (2001) Wagstaff & Lopez (1996)	Chirikos & Sear (2000) Herr (2008)

[a] The paper carried out VRS, however, effectively CRS specification results since variables are in ratios. SFA is carried out in Jacobs (2001) too, however, with linear functional specification.

Chapter 3

Data

This chapter introduces the data set, input and output variables used, as well as provides descriptive statistics.

3.1 Data Set

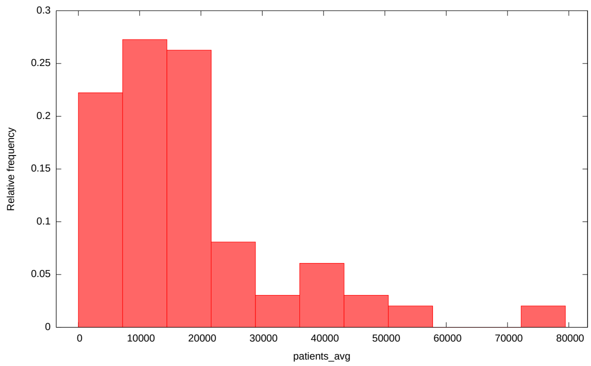
This thesis evaluates efficiency of hospitals in the Czech Republic. The data on individual hospitals was obtained from the Institute of Health Information and Statistics of the Czech Republic (further 'UZIS')[1], specifically from the following two publications: 'Healthcare - Regions and the Czech Republic' ('Zdravotnictví kraje + ČR') for individual years and 'Operational and Economic Information on Inpatient Facilities in Regions' ('Provozně-ekonomické informace lůžkových zaříení v ... kraji').[2] In overall, the selected hospitals were observed for the period of 2001–2008. Only general hospitals were included as in Afonso & Fernandes (2008); Herr (2008); Frohloff (2007). Specialized clinics and nursing homes were excluded to ensure a considerably homogeneous sample. Furthermore, hospitals which did not provide data information for at least one year were excluded as well. The data set was subsequently reduced for hospitals which did not include data on the patient day mix in 2005 as of 'Operational and Economic Information on Inpatient Facilities in Regions' from UZIS. Thus from 140 Czech hospitals initially considered, 30 % was excluded for the above stated reasons resulting in 99 units. The final list of hospitals analyzed in this thesis is provided in Table A.1. Most of the hospitals treat up to 20,000 patients a year on average. The distribution of hospitals in terms of

[1] www.uzis.cz

[2] Both of these data sources will jointly be referred to as data from UZIS in the text.

size is depicted in Figure 3.1.

Figure 3.1: Size Distribution of Hospitals



The thesis analyzes the data using two methods, therefore, the dataset was adjusted accordingly. It was divided into 8 cross-sectional sets based on the year of observations, i.e. 2001–2008, for the purposes of DEA. Number of observations in each cross section is provided in Table 3.1. An unbalanced panel of 99 hospitals observed for 8 years was used for SFA. The unbalanced panel comprises 661 full observations.

Table 3.1: Number of Observations - Cross Sections 2001-2008

Cross-section	# Obs.
2001	76
2002	82
2003	79
2004	84
2005	84
2006	90
2007	78
2008	88

Most of the data used as determinants of inefficiency was obtained from the Czech Statistical Office, Regional Yearbooks. Data concerning ownership and profit status was obtained from the Registry of Companies in the Czech Republic which is available online.[3]

Data expressed in monetary terms, i.e. costs and salaries, was adjusted for inflation using the annual growth rate of inflation with 2001 representing the

[3] Available at www.obchodnirejstrik.cz.

base year. The adjustment takes place both for the purposes of DEA and SFA.[4]

As Table 3.2 reveals, majority of the studies reviewed estimated cross sectional efficiency. Panel estimation was not that frequent. This thesis will, however, estimate a panel[5] employing SFA, and carry out a panel-like estimation with DEA. In other words, since DEA is unable to handle panel data, there is a number of ways how this kind of data can be treated. For instance, efficiency can be estimated year by year and consequently averaged over the period of observation to obtain the overall score as in Hofmarcher *et al.* (2002). Another possibility would be to rank the results and compare the time series correlation of ranks as in Magnussen (1996). As suggested and performed by Chirikos & Sear (2000), it is also possible to pool the entire panel when inter temporal changes are adjusted for differences in inflation using Purchasing Power Standards (PPS) or another similar method. This thesis finds the methods employed by Hofmarcher *et al.* (2002) and Magnussen (1996) quite appealing. Depending on purpose, results will be averaged over the period or DEA ranks for each year will be obtained and correlations of these ranks consequently calculated.

Efficiency will be estimated with Coelli *et al.*'s software. For DEA, software DEAP Version 2.1 (Coelli 1996a) and for SFA software FRONTIER Version 4.1. will be used (Coelli 1996b). For preliminary analysis statistical softwares R 2.8.1 (R Development Core Team 2006) and Gretl (Cottrell & Lucchetti 2007) will be used.

[4]However, adjustment for DEA is not necessary since only cross-sections are analyzed.

[5]The benefits of a longitudinal study have been acknowledged even by studies which employed cross-sectional analyses. Using a panel or a cross-section is mainly driven by the purpose of the study.

Table 3.2: Dataset Used for Frontier Estimation in the Literature

Cross-section	Panel
Dlouhý *et al.* (2007)	Farsi & Filippini (2004)
Linna *et al.* (2006)	Hofmarcher *et al.* (2002)
Rosko & Chilingerian (1999)	Magnussen (1996)
Yong & Harris (1999)	Zuckerman *et al.* (1994)
Valdmanis (1992)	Chirikos & Sear (2000)
Vitaliano & Toren (1996)	Rosko (2001)
Kooreman (1994b)	Wang *et al.* (1999)
Prior (1996)	Wagstaff & Lopez (1996)
Cellini *et al.* (2000)	Parkin & Hollingsworth (1997)
Frohloff (2007)	Janlov (2007)
Herr (2008)	Herr (2008)
Nayar & Ozcan (2008)	Afonso & Fernandes (2008)
Kontodimopoulos *et al.* (2006)	
Blank & Valdmanis (2005)	
Jacobs (2001)	
Mortimer *et al.* (2002)	
Staat (2006)	

Note: When efficiency estimates were calculated in cross-sections and ranks further compared, it is considered a panel-like estimation here and thus included in the column 'Panel'.

3.1.1 Input & Output Variables & Determinants

Input Variables

There exists a number of ways to account for inputs in frontier efficiency estimations. These possibilities are however dependent on the method employed. DEA can accommodate multiple inputs, also in physical terms, while SFA requires an aggregated single variable for input oriented efficiency calculations.[6] Inputs in physical terms can include the number of employees (disaggregated into doctors and nurses, or even into more categories as in Kooreman (1994b) or Valdmanis (1992); non-medical staff (administrative and other personnel)) and capital inputs which is very often approximated by the number of beds. Using multiple inputs in physical terms, technical efficiency is measured which proves highly appropriate where information on input prices is not available. Aggregation of the input variables, required by the SFA, is usually represented by total costs. In other words, cost efficiency is measured. When a decision whether to employ multiple inputs or total costs can be made, aggregation

[6] The difference in input variables used for DEA and SFA is obvious with Chirikos & Sear (2000) who used disaggregated inputs for DEA and total costs for SFA.

of the input variable into total costs is appropriate primarily for a long-term analysis since in the long-run hospitals can decide on the employment of an efficient mix of inputs. This thesis employs the only input variable - total operating costs (denoted as 'costs' in the analysis)[7] both for DEA and SFA. It does so for the purposes of comparability of the results obtained from the two methods. The motivation for total costs was firstly driven by data availability but at the same time, it is believed that an 8-year panel to a certain extent fulfills the criteria of a long-term analysis. During this period, restructuring and privatization of hospitals often took place and thus hospitals could decide on a more efficient employment of resources.

Total operating costs were calculated from the data from UZIS. UZIS regional yearbooks contain information on the operating costs per patient day which UZIS calculate as:

$$L\frac{1+\frac{D+J+N}{L+A}}{T} \tag{3.1}$$

where L are costs for inpatient care, D costs for medical transport, J costs for other medical care, N costs for non-medical procedures, A outpatient costs and T number of inpatient days.

UZIS acknowledge that this method to obtain operating costs per patient day is not absolutely accurate from the economic point of view. However, it suffices for the purposes of this thesis since inpatient costs are not obtainable otherwise. Furthermore, since the calculation method is the same for all hospitals, using this data should not result in major difficulties.

Total operating costs were thus calculated as a multiplication of operating costs per patient day, the number of admissions and the average length of stay. Total operating costs represent a dependent variable for the analysis

Even though majority of hospitals in the Czech Republic are still publicly owned, or regions are their major shareholders, the data availability particularly in the sphere of operating costs is not overwhelming. Since some hospitals missed information on costs only for some years, they were still left in the dataset and an unbalanced panel was used.

[7] Including all inpatient costs excluding capital costs.

Output Variables

Ideally, health output should be measured as an increment to patient health status, i.e. as final products of hospitals. However, since this is technically impossible to measure, in all hospital efficiency studies intermediate outputs of various kinds are used instead.

Many studies use outputs disaggregated into output from inpatient, outpatient and acute care. Examples include Hofmarcher *et al.* (2002), Prior (1996), Chirikos & Sear (2000), Vitaliano & Toren (1996), Linna *et al.* (2006), Farsi & Filippini (2004), Zuckerman *et al.* (1994), Nayar & Ozcan (2008) or Rosko (2001). However, such a complex definition of hospital output is impossible in our case due to limited data availability. However, Yong & Harris (1999) found out that the inpatient care consumes majority of hospital resources. These findings are supported by the data on economic information provided from UZIS (2005), which disaggregate hospital costs into inpatient, outpatient, transport costs and non-medical expenses. Inpatient costs of Czech hospitals are around 50 % of total costs on average. Of the remaining categories, outpatient care accounts for 15-20 % of total costs, the rest is taken up by transportation costs and non-medical expenses. One should also keep in mind in this context that the available input variable employed in this thesis is adjusted to inpatient care. Because of all these reasons, we employ inpatient care exclusively.

In the studies surveyed, inpatient output was approximated either by the number of admissions, i.e. number of patients treated, or the number of inpatient days[8]. Additionally, Chirikos & Sear (2000) employs the number of patient days while also distinguishing the first day of admission assuming that the majority of resource intensity of care is attributable to that day.[9]

There has not been much discussion on which of these two variables (inpatient days, number of admissions) should be preferable, however some controversies appear. Specifically, Zuckerman *et al.* (1994), Farsi & Filippini (2004) and Hofmarcher *et al.* (2002) suggest that the number of patients should rather be

[8]It is obtained by multiplying the number of admissions and the average length of stay.

[9]Even though Chirikos & Sear's specification is considered viable, this will not be considered here due to data limitations. Specifically, the number of admissions could not be retrieved in division to wards since patients which were transferred from one ward to another were calculated as two people for the hospital as a whole, each time for the ward concerned. Including one patient multiple times would bias the results.

employed due to possible endogeneity in the number of patient days. In other words, the length of stay, which to a certain extent reflects how patients are treated, is in the direct control of the hospital, and thus the inefficiencies of production function are transferred into output and thus are likely to be correlated with the inefficiency term of the cost function.

On the other hand, Magnussen (1996) points out that the number of inpatient days is assumed to be better since they are “a more medically homogeneous units” (Magnussen 1996, p. 30). Additionally, the length of stay could be connected with the complexity of the cases treated as well as differences in management, aspects which the number of patients specification would not take account of.

Based on the discussion, this thesis assumes that endogeneity is rather unlikely since hospitals are place constrained rather than deciding on the length of stay themselves and thus transferring inefficiency into their production function. Moreover, in the context of Czech hospitals competition in health care coverage does not work and thus hospitals do not choose among patients with shorter or longer length of stay in order to influence their efficiency. In addition, as the initial analysis of the data in Chapter 4 reveals, the correlation of the inpatient days and the number of patients is considerably high. Moreover, the structure of correlation as revealed by the Principal Component Analysis (further ‘PCA’) in Chapter 4 is also similar. Therefore, only inpatient days will be used in this thesis.[10]

It is without doubts that some kinds of medical treatments are more expensive than others, which accounts for further variations in costs. Rosko & Chilingerian (1999), Valdmanis (1992) and Hofmarcher *et al.* (2002) claim that weighting according to severity of cases is absolutely vital for the efficiency analysis. Furthermore, when analyzing Norwegian hospitals, Magnussen (1996) proved that the choice of weighting criteria has an effect on the resulting individual efficiency scores and ranks. Specifically, he found rank correlation between efficiency scores obtained using two different weighting criteria (surgical and medical patient days; and simple and complex patient days) to be only 0.78.

[10]Patient days were provided in disaggregation into wards in UZIS (2005), while the number of disaggregated patients had to be calculated from the same publication. Therefore, when deciding only one type of output, for all the above stated reasons, patient days were preferred.

Inpatient output was found to be adjusted according to various weighting and aggregating criteria, such as according to the diagnostic related groups (further 'DRG'), i.e. case-mix adjusted groups as in Hofmarcher *et al.* (2002), Vitaliano & Toren (1996), Farsi & Filippini (2004), Linna *et al.* (2006); medical/surgical or simple/complex case as in Magnussen (1996); the types of patients treated as in Kooreman (1994b). Mostly[11] the weighted output was aggregated into a single variable. Nevertheless, Rosko & Chilingerian (1999) suggested that the optimal way to account for differences in severity of output should be to use a matrix of the DRG groups and employ them as such into the analysis.[12] Nevertheless, such a method of dealing with differences in severity of output has not widely been applied in the literature since too many explanatory variable cause an extensive loss of the degrees of freedom in SFA and a possible bias in DEA.

This thesis will weight the number of patient days according to the case-mix criteria as of UZIS (2005) publications, which disaggregates total inpatient days into non-operative wards ("non_op_days"), operative wards ("op_days"), intensive care ("intense_days") and nursing care/long-term care ("nursing_days"). The disaggregation as of economic information by UZIS (2004) slightly differs dividing inpatient days into basic care, specialized care, intensive care and nursing/long-term care.[13] However, since the share of intensive care and nursing/long-term care from the total, the two categories which were kept the same in both years, were found to be considerably stable, (share of intensive care with correlation of 0.98, nursing care was correlated by 0.85 between 2004 and 2005) the shares of the remaining two variables were not expected to differ much temporarily either. The obtained weights as of UZIS (2005) will thus be applied for the whole sample and the total number of patient days for the remaining years will be divided accordingly. In the end however, only the number of nursing days will be used as a separate variable in the analysis. Number of non-operative, operative and nursing days will be summed and used jointly ("sum_3_days"). Chapter 4 deals with the analysis of disaggregated patient days extensively and provides reasons for summing up the first three types of care.

Besides the weighted number of patient days, there are other variables expected

[11] Except for Kooreman (1994b) from the studies cited above.

[12] Under similar rationale, Kooreman (1994b) distinguished a vector of four output types.

[13] Information for other years was not available.

to influence inpatient costs of hospitals and, at the same time, increase output. These include for instance indicators of the quality of care, which will therefore also be included into the analysis as output variables[14]. Specifically, quality of care is likely to increase costs of hospitals, however at the same time, output of higher quality can be considered as more output. Quality of care was accounted for differently in the literature. For instance Zuckerman *et al.* (1994) included mortality rates. Vitaliano & Toren (1996) employed technology index and occupancy rate, which is defined as the ratio of the actual patient days to the maximum patient days possible. In other words, it reveals whether the hospital operates with an excess capacity.[15]

Quality of care variables used in this thesis will comprise per day doctor/bed and nurse/bed ratios as in Frohloff (2007); and the level of technology, consistent with Vitaliano & Toren (1996). The doctor/bed and nurse/bed ratios were calculated from the data from UZIS. First the total number of beds per doctor/nurse was obtained and consequently inverted, since we are interested in maximizing output. In other words, the variable was transformed as to be positively related to costs. Basically, the more doctors/nurses attend one bed per day, the higher the quality of care is assumed to be.

The technology index is included since it is assumed that the complexity of technology is insufficiently accounted for by the output used. However, since the data for this index is available only for the year 2004 and for selected hospitals only, the significance of the technology index will be tested on a cross sectional sample for the year 2004 only.

Two technology indices will be applied, specifically equipment/10,000 patients (further referred to as 'TI_equip') and procedures/patient (further referred to as 'TI_proced').[16] The choice of technological indices weighted by the number of patients was driven by the notion that weighting by patients can account for the quality of care better. In other words, if a hospital owns technological

[14] The same methodology, even though with different quality variables, was followed by Nayar & Ozcan (2008).

[15] Other studies employ occupancy rate as a determinant of efficiency, for instance Zuckerman *et al.* (1994) and Yong & Harris (1999), believing that it does not increase output but rather has an effect on inefficiency.

[16] Four different technology indices were initially considered, i.e. the number of equipment, equipment per 10,000 patients, the number of procedures and the number of procedures per patient.

equipment but does not employ it or does not have personnel which can attend it professionally, the quality of care does not increase meaning that illnesses are not detected soon enough, etc. That is to say, when not used sufficiently enough, equipment is connected only with costs but does not increase output which is not of a concern here. Furthermore, the more equipment per patient the hospital has, the more likely it is to have medical stuff which is trained and specialized in using the equipment concerned. It is believed that the two variables capture considerably different phenomena.[17]

Only demanding technical equipment was considered as technical equipment - x-ray computer tomography, mammography, magnetic resonance imaging, surgery and theraupeutical lasers. This data was obtained from UZIS Economic Publications (2004). It is important to keep in mind, however, that this technical equipment is used by ambulatory patients as well. But it is believed, that some information is still revealed when employed only for the analysis of inpatient care.

The technology indices were calculated such that the highest number of equipment/procedures on each equipment in the cross-section is set equal to 1. The respective equipment of the rest of the sample is compared to it. The overall technology index is obtained by averaging the individual indices.

The intention was to use also the total number of empty bed days as in Vitaliano & Toren (1996), where the occupancy rate variable was used. The rationale for employing this variable when measuring cost efficiency here is justified by the fact that even though having empty beds increases costs, it at the same time increases the quality of output. In other words, if there are empty beds in a hospital, an admitted patient is likely to be put into a separate room and thus is provided with a higher quality of care. Moreover, doctors devote more of their time and effort to each patient. Unfortunately, this variable had to be excluded after the very first analysis of the data since it was strongly correlated with patient days.

Having provided a description of input and output variables, descriptive statistics is provided in Table 3.3. Table 3.4 shows a correlation matrix of all outputs employed, including technology indices. Table A.2 provides overview and summary of all variables used. The relationship between input and output variables

[17] Their correlation is 0.658 as obvious from Table 3.4.

Table 3.3: Descriptive Statistics - Input & Output variables

Variable	No. obs.	Mean	Median	Minimum	Maximum	Std. Dev.
costs	661	5.072E+08	2.971E+08	4.037E+07	3.506E+09	6.090E+08
sum_3_days	661	135200	93795	16062	607026	115660
nursing_days	370	17490	14937	3892	52470	10472
doctor_10_beds	660	1.4728	1.3998	0.4370	3.7606	0.3878
nurse_10_beds	660	5.3495	5.1632	2.6329	13.7757	1.0805
TI_equip	70	0.1648	0.1543	0.0186	0.4250	0.0924
TI_proced	65	0.1048	0.0956	0.0020	0.3552	0.0753

Note: Technological Indices available for 2004 only

Table 3.4: Correlation Matrix - Outputs

sum_3_days	nursing_days	doctor_bed	nurse_bed	TI_equip	TI_proced	
1	0.203	0.3359	0.3641	0.4729	0.3396	sum_3_days
	1	-0.0405	-0.1028	0.1233	0.0195	nursing_days
		1	0.6586	0.5089	0.5134	doctor_bed
			1	0.5156	0.546	nurse_bed
				1	0.658	TI_equip
					1	TI_proced

is depicted in Figure A.1.

Determinants of Inefficiency

When evaluating efficiency of a set of hospitals, it has to be acknowledged that the results might be specific to their nature or inherent characteristics, as well as the environment in which they are situated. Various determinants of inefficiency have been employed in the literature. The choice of variables used as potential determinants in this thesis has been guided by empirical papers in the sphere of health care and data availability. In what follows, variables are divided into two groups, i.e. those linked to the hospital and those identifying the environment in which the hospital is situated. They include:

- Teaching Status ("teaching")

Teaching hospitals tend to reveal a different structure of services providing less of basic and more of highly specialized care, management and organization of resources. (Vitaliano & Toren 1996, p. 165). Therefore, the presence of teaching status has been acknowledged as a very important determinant of efficiency. In some studies, however, teaching status has been included into the main estimation under the assumption that teaching status represents another kind of output which cannot be captured by the volume and case-mix variables (see for example Vitaliano & Toren (1996)). Nevertheless, this thesis favors rather the former. Using teaching status as a determinant of efficiency is further supported by Rosko & Chilingerian (1999) who state that when employing teaching status in efficiency analysis, one is interested in how 'historic mission' (i.e. teaching commitment) affects the hospital's position vis-a-vis the best practice production frontier'. Including teaching variable in the cost function thus precludes this type of assessment. The assumption of this thesis is consistent with findings of Rosko (2001) that teaching status increases inefficiency.[18]

- Size ("size1", "size3")

For the purposes of this thesis, hospitals were divided into three groups according to size. The logics behind is consistent with Farsi & Filippini (2004). The number of beds and the number of treated patients were found to be correlated by 98.2 %. Therefore, division according to either of the categories does not make much difference. Hospitals were divided according to the number of patients treated. Group intervals as well as the number of hospitals included in each group are provided in Table 3.5 and thus supplement the frequency plot provided in Figure 3.1. Categorization of individual hospitals is provided in Table A.5. It is worth pointing out, that all of the teaching hospitals are classified in group 3. Furthermore, there are two very big hospitals included in the sample, namely observations 25 and 91. They treat over 70,000 patients a year. The third biggest hospital cures 'only' 54,700 patients a year. Furthermore, most of the analyzed hospitals treat up to 20,000 patients a year. In the analysis only two size dummies will be included at a time, specifically for the group of the smallest hospitals and the group of the biggest hospitals, to avoid linear combinations of variables.

Table 3.5: Size Groups

Group	Interval	# Obs.
1	$\leq$ 10,000	33
2	10,001–20,000	33
3	$>$ 20001	33
	total	99

[18] Initially, also military dummy was considered since it was assumed that also military hospitals reveal a different structure of health care provision. However, only 3 % of all Czech hospitals are classified as being of military status, namely observation 26, 36 and 93. Furthermore, when tested, the effect was not significant, therefore, this variable was excluded for the final analysis.

According to the economies of scale rationale, one would expect that as size of a hospital increases, efficiency increases. This hypothesis was proved by Zuckerman *et al.* (1994) and Vitaliano & Toren (1996). On the other hand, using available beds to account for size, Yong & Harris (1999) found out that it decreases efficiency. Yong & Harris's findings could be explained by the presence of other costs to manage complexity of a larger scale practice, such as professional administration, information technology demands, infrastructure, etc.

The mixed empirical findings, suggest that size effect is region-specific. Therefore, either of the effects is expected, i.e. that size decreases inefficiency due to economies of scale effect, or that size increases inefficiency due to increased costs connected with the management of complex care.

- Ownership Type

Keeping in mind transformation of many of the Czech hospitals into joint stock companies starting in 2004, ownership dummy is expected to explain a significant portion of inefficiency because the main purpose of privatization was to curb costs and increase efficiency. It is interesting to point out that many of the hospitals which were transformed anytime during the period examined, changed their status in 2006, 23 out of 41. Overview of hospitals which underwent the process of transformation in 2006 is provided in Table A.3.[19]

Even though empirical literature (Zuckerman *et al.* 1994; Rosko & Chilingerian 1999; Rosko 2001; Frohloff 2007) come to the conclusion that private hospitals are less cost efficient than public hospitals, it has to be kept in mind that even though many Czech hospitals have been transformed into joint-stock companies, regions, district or municipalities are their major shareholders. Therefore, they are still to a large extent publicly owned.

Ownership status will be accounted for by a dummy variable, which will capture the not-for-profit public status ('not_profit'). The hypothesis is that not-for-profit public status has a positive effect on inefficiency. Having carefully examined individual hospitals, it has been found that there are only 5 % of hospitals which are for-profit while being owned by a private entity at the same time. Thus no varible to capture private for profit ownership will be used, even

[19] This number includes also hospitals 52, 75, 77, 79, 82 which were formally privatized in July 2005 and thus classified as being for-profit already in 2005, however, the process of transformation is likely to be carried out primarily in 2006.

though initially considered.[20] Accounting for the effect of not for profit public ownership, the effect of privatization on inefficiency can be uncovered.

The remaining determinants express attributes of the environment in which the hospital is situated.

- Population ("population")

Data on population was gathered for municipalities where hospitals are situated. Since Prague was taken as one municipality and thus its population was expected to bias the results, the population of Prague was divided into core catchment areas of individual hospitals. Specifically, the total population of Prague was split according to the share of patients treated in each of the Prague's hospitals.

Population is expected to capture multiple effects on inefficiency, both positive and negative. An expected positive effect on inefficiency is connected with longer waiting times for treatments, both for outpatient preventive care as well as inpatient care. The longer the waiting times, and thus the later the illness is uncovered and treated, the lower the change of full recovery at a reasonable cost. A positive effect on efficiency, on the other hand, is expected to be represented by the availability of more advanced and modern technologies used for diagnostics and treatments. The process of treatment thus becomes more efficient. The results are expected to depend on which of the two effects (positive or negative) is likely to overweight.

- Population over 65 Years of Age ("over_65")

This variable is expressed as a proportion to the total population in the municipality. It is assumed that more people over 65 in municipality increase inefficiency of hospitals since the elderly require usually more demanding and costly treatments such as bypass, recovery after heart-attack, stroke, etc.

[20] Furthermore, a dummy variable capturing public ownership regardless of the form, i.e. not-for profit or for-profit, was tested resulting in an insignificant effect since 95 % of hospitals belong to this group.

- Unemployment Rate ("unempl")

Unemployment rate was gathered for districts of municipalities with extended powers since the data was not available for municipalities in the narrow sense. The assumption on the effect of unemployment on inefficiency is based on the rationale that higher unemployment rate increases opportunity costs of being sick and thus not working due to increased competition in the labor market. Thus higher rate of unemployment increases efficiency of hospitals since the people are more interested in their health, take advantage of preventive care and generally avoid long-term and costly hospital treatment.

- Salary ("salary")

Average monthly wages were gathered for districts. However, the Czech Statistical Office provides data only till 2004 in this aggregation. From 2005 the data is not statistically collected anymore and only regional information is available. Therefore, for the remaining years, i.e. 2005–2008, information from 2004 was adjusted for an annual growth of the average wage in the region. This approximation is considered to be sufficient for the analysis. The data was adjusted for inflation with 2001 representing the base year.

Average salary in the region is assumed to be correlated with salaries of medical personnel. Therefore, a positive effect of salaries on inefficiency is anticipated.

- Competition ("competition")

Consistent with Zuckerman *et al.* (1994), the number of hospitals in the region will represent a proxy for competition. A higher number of hospitals is assumed to increase efficiency. The rationale is based on the assumption that if a public hospital is inefficient, its existence is threatened, for it competes for government finances with other public hospitals.[21]

Descriptive statistics for determinants of inefficiency is provided in Table 3.6. Correlation matrix of determinants is depicted in Table 3.7. Furthermore, Table A.2 summarizes besides input and output variables also determinants of

[21] In this context, the significance of the number of hospitals in the region weighted by regional population was tested. However, the variable proved insignificant. It is assumed that if the number of hospitals in the region was weighted by distances to other hospitals, the variable might be significant. Unfortunately, this data is not available and the discussion thus serves as a motivation for further research.

inefficiency used in this thesis. To provide full information, a matrix of correlation of outputs and determinants of inefficiency is provided in Table A.6.

Table 3.6: Descriptive Statistics - Determinants of Efficiency

Variable	Mean	Median	Minimum	Maximum	Std. Dev.
teaching	0.1241	0	0	1	0.3299
size1	0.3147	0	0	1	0.4647
size3	0.3570	0	0	1	0.4791
not_profit	0.7216	1	0	1	0.4485
population	65255	27544	3107	373272	89686
over_65	14.173	14.250	8.800	18.300	1.650
unempl	8.8909	7.9700	2.1400	24.2000	4.3967
salary	15897	15463	11894	24416	2572
competition	15.912	14	5	28	6.7074

Table 3.7: Correlation Matrix - Determinants

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
1	-0.255	0.505	0.2337	0.6352	0.3526	-0.2277	0.4818	0.2562	teaching (1)
	1	-0.5049	-0.3278	-0.2974	-0.0655	0.0425	-0.1338	-0.0665	size1 (2)
		1	0.2937	0.4456	0.0891	-0.0006	0.2961	0.1181	size3 (3)
			1	0.2735	-0.0628	0.1231	-0.0269	0.1843	not_profit (5)
				1	0.3355	-0.0353	0.4478	0.3317	population (6)
					1	-0.476	0.4357	0.0713	over_65 (7)
						1	-0.4465	0.0861	unempl (8)
							1	0.4375	salary (9)
								1	competition (10)

Chapter 4

Preliminary Analysis

Before an efficiency analysis could be carried out, the quality of the data had to be thoroughly analyzed. Chapter 3 described the final dataset, however certain changes to the original data were necessary. Chapter 4 comments on the process of adjustment of the data.

As for the data on input and outputs, correlation of different types of output was taken care of, so that these variables could be used in the parametric model. Furthermore, finding out correlations among outputs and thus the possibility to decrease dimensionality, is also beneficial for DEA. The correlation between the two sets of output variables initially considered, i.e. patients and patient days, was high, so only one set of these outputs was decided on. Furthermore, as suggested in Chapter 2 the presence of outliers might cause serious consequences for the frontier models. Outlier detection was thus also carried out.

4.1 Multicollinearity of Output Variables

Initially two sets of output variables were considered, namely the number of patients and the number of patient days divided into wards. The number of patients and the number of patient days in total proved highly correlated with each other, with the correlation coefficient 0.9808.

Examining the different kinds of output (i.e. non-operative, operative, intensive, nursing), a high level of correlation among the first three was discovered both for the number of patients and patient days. For the remaining outputs, i.e. the number of doctors per bed, the number of nurses per bed and selected

Table 4.1: Correlation Matrix - Patient Days

non_op_days	op_days	intense_days	nursing_days	
1.0000	0.9292	0.8777	0.1666	non_op_days
	1.0000	0.9317	0.2499	op_days
		1.0000	0.2020	intense_days
			1.0000	nursing_days

Table 4.2: Correlation Matrix - Patients

non_op_patients	op_patients	intense_patient	nursing_patient	
1.0000	0.9288	0.8859	0.0651	non_op_patients
	1.0000	0.9512	0.1109	op_patients
		1.0000	0.1265	intense_patient
			1.0000	nursing_patient

technology indices, the correlation was by no means high as was depicted in Table 3.4.

Table 4.1 and Table 4.2 provide correlation coefficients only among the 4 kinds of output, for patient days and patients respectively. Figure A.2 and Figure A.3 further depict this correlation.

It results that certain adjustments of the types of output were necessary since otherwise multicollinearity would result in the SFA regression if all were employed separately. At the same time, it was highly desirable to restructure the data in such a way to keep as much information in the analysis as possible to account for the output mix. So the correlation matrix and plots were further supplemented by the Principal Components Analysis (further 'PCA') to discover the exact internal structure among these variables taken together.[1] Shortly, PCA projects the data on the new coordinate system such that the greatest variance lies on the first coordinate which is expressed by the first component. The second greatest variance is explained by the second component which is however uncorrelated with the first one and so on. Consequently, only the greatest variances are taken into account and thus the original set is transformed into a lower dimensional data not correlated with one another.[2] Table 4.3 and Table 4.4 provide the results for patient days and patients in

[1] PCA is very suitable for high dimensional data since projecting more than three dimensions together is graphically impossible. For explanation of PCA see Jolliffe (2002).

[2] A similar approach to multicollinearity was taken by Janlov (2007) in order to reduce the dimension of the input and output matrix and thus reduce the bias in DEA results.

natural units.

Table 4.3: Principal Components Analysis - Patient Days

Eigenanalysis of the Correlation Matrix

Component	Eigenvalue	Proportion	Cumulative
1	2.9353	0.7338	0.7338
2	0.9414	0.2353	0.9692
3	0.0767	0.0192	0.9884
4	0.0466	0.0116	1.0000

Eigenvectors (component loadings)

Variable	PC1	PC2	PC3	PC4
non_op_days	0.566	0.139	0.559	0.589
op_days	0.568	0.048	−0.797	0.199
intense_days	0.570	0.119	0.218	−0.783
nursing_days	0.177	−0.982	0.067	−0.001

Table 4.4: Principal Components Analysis - Patients

Eigenanalysis of the Correlation Matrix

Component	Eigenvalue	Proportion	Cumulative
1	2.8902	0.7226	0.7226
2	0.9850	0.2463	0.9688
3	0.0835	0.0209	0.9897
4	0.0413	0.0103	1.0000

Eigenvectors (component loadings)

Variable	PC1	PC2	PC3	PC4
non_op_patients	0.570	0.085	−0.804	−0.150
op_patients	0.576	0.045	0.529	−0.621
intense_patients	0.579	0.031	0.270	0.769
nursing_patients	0.093	−0.995	−0.037	−0.017

PCA on both patient days and patients revealed similar results. Furthermore, the results obtained again confirm the high degree of correlation between patient days and patients as such. Not only do the data reveal a considerably same structure, but the component loadings for the individual variables are also to a large extent consistent. This thesis will thus employ only one set of output variables for the subsequent analysis - patient days.

It is obvious from the results on proportions of the eigenvalues of the correlation matrix that the first two components express over 96.92 % of information about the data. One could therefore transform the four initial variables and include only two types of care. The first component loadings are assumed to express variance in the first three variables, while the second ones account for the variance in nursing days. When looking at loadings for the first component, their similarity for the three variables concerned (non-operative, operative intensive care) is striking. Instead of multiplying the original variables by their loadings for each of the two most significant components, one could thus simply transform the data by summing up the non-operative, operative and intensive days. The thesis thus accounts for the internal structure of the data exactly this way and so the dimensionality of inpatient days is reduced from four to two. A new variable 'sum_3_days' accounting for the three types of care is created and used in the analysis together with the variable expressing nursing days.

4.2 Outlier Detection

Frontier analyses, non-parametric methods in particular, are very sensitive to outliers. Outliers, i.e. points with low probability of occurrence, are however not perceived as absolute ill in frontier models. Very often, they may represent the most interesting parts of the data, which deserve further attention.

For the purposes of outlier detection analysis, patient days were adjusted in the same way as for the analysis itself (i.e. the first three types of care were summed). Outlier detection was employed for cross-sectional sets only since comparing these within and between observations in the panel does not have much justification.

As pointed out by Fried *et al.* (2008, p. 497) "it is unlikely that a single method will be able to find all outliers in all instances especially when the number of dimensions is large". Moreover, different methods very often concentrate on outliers from different perspectives. Therefore, two outlier detection methods were employed in this thesis, namely a method based on order-m frontiers as developed by Simar (2003) and an outlier detection method as developed by Wilson (1993). The results for both methods were obtained using FEAR Package which was developed by Wilson (2008). The package allows frontier estimations and can be incorporated into the econometric software R.

Simar's method to detect outliers uses the rationale of partial frontiers. That is, instead of focusing on a single frontier, alternative numerous partial frontiers formed from the data are considered. The idea was first proposed by Cazals *et al.* (2002) as a robust alternative to traditional non-parametric frontier estimators (DEA, FDH).

Such a partial frontier is determined by observations randomly extracted from the sample, $m \geq 1$. Furthermore, the number of repetitions (by default set to 200) over which the resulting frontier is normalized (usually solved by Monte-Carlo replications) needs to be set. Having established a significance level, if an observation remains outside the order-m frontier as m increases, such an observation may be an outlier - i.e. a super efficient observation which unreasonably influences the efficiency frontier. Simar (2003) defines the order-m frontier as follows:

$$\phi_m = E[\min(X^1, \ldots, X^m] = \int_0^\infty [S_X(x)]^m \, dx \tag{4.1}$$

where

$$S_X(x) = \text{Prob}(X \geq x) = 1 - F_X(x) \tag{4.2}$$

where $F_X(.)$ denotes a distribution function of X, $S_X(.)$ is a survival function; $x = (x_1 \ldots, x_n)$ denotes a sample of observed values.[3]

In other words, the expected minimum achievable input level, ϕ^m, i.e. the lower boundary for X, is calculated as the expected value of the minimum of m random variables $X^1, \ldots, X^m$ drawn from the distribution function of X. Sometimes, m random variables $X^1, \ldots, X^m$ are drawn from the conditional distribution function of X given $Y \geq y$. In this case, not all observations in the sample are considered.[4]

The results for the Simar (2003)'s analysis for the cross-section of 2008 under $m = 25$ revealed efficiency greater than 1.1 [5] with 9 observations. However, with increasing m, the efficiency of all superefficient observations tended to decrease. With $m = 75$ the highest efficiency obtained was 1.05 which is considered insignificant. No observation was thus classified as outlier using Simar (2003)'s outlier detection method. The same analysis was carried out for the remaining cross-sections. As expected, the results revealed very similar trends, i.e. there were some super efficient values under $m = 25$ but the number was decreasing with increasing m.

[3] There is no *a priori* relations between m and n. m is a trimming parameter fixed at any desired level, whereas n is the sample size.

[4] For further discussion see Simar (2003) or Fried *et al.* (2008).

[5] The significance level was set at 10 %.

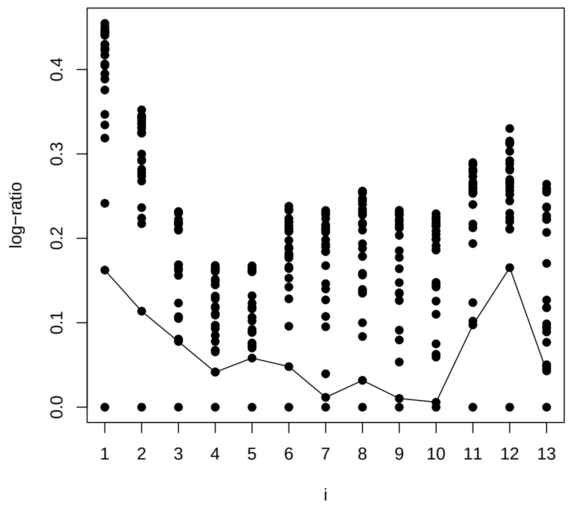
The outlier detection method according to Wilson (1993) employs the influence function based on the geometric volume spanned by the sample observations and the sensitivity of this volume with respect to deleting suspicious observations (in singleton, pairs, triplets, etc.) from the sample. Log-ratio is expressed as:

$$\log[R_L^{(\ell)}(\mathbf{Z}^{*\prime})/R_{min}^{(\ell)}] \tag{4.3}$$

where $R_{min}^{(\ell)} = \min_L\{R_L^{(\ell)}(\mathbf{Z}^{*\prime})\}$ and $R_L^{(\ell)}(\mathbf{Z}^{*\prime})$ represents the proportion of the geometric volume in the input-output space spanned by a subset of the data obtained by deleting the ℓ observations with indices in the set L, relative to the volume spanned by the entire set of n observations.

The results can be graphically analyzed where log-ratios are expressed as a function of the number (i) of deleted observations (ℓ). A detailed mathematical description of the method is can be found in Wilson (1993) or Fried *et al.* (2008).

Figure 4.1: Outlier Detection Wilson (1993)
- 2008 Cross-Section Results



Being grounded on different principles, the analysis based on Wilson (1993) for the cross-sectional set of 2008 did not reveal identical results to Simar (2003) for the same cross-section. Deleting suspicious observations one by one, the analysis was carried out up to 13 omitted observations. Deleting more observations was computationally intractable in the econometric software R - at the same time getting rid of 13 observations for the sample for 2008 is too much anyway.

The results for Wilson (1993)'s method provide interesting findings. In Figure 4.1, the line connects the second smallest values for each i to illustrate the separation between the smallest ratios for each i. The larger the distance, the more likely there is to be an outlier among the remaining observations.

Figure 4.1 identifies 12 outliers for the cross-section of 2008, two groups of which are most significant, namely observations 1 to 6 and 11 to 12. Scrutinizing these results, only teaching hospitals, one military hospital and one very large hospital are identified as potential outliers for the cross-section of 2008. It therefore suggests that they can hardly be excluded from the set. They are merely hospitals of different characteristics and nature. Having carried out analysis for the remaining cross sections, Wilson's method again identified teaching and large hospitals as outliers. The proposed outliers will therefore be kept in the sample for the the analysis. Consequently, the SFA analysis will account for these differences using determinants of inefficiency.

Chapter 5

Results

This chapter comments on the results of the analysis. The thesis investigated individual hospitals using DEA and SFA and SFA with determinants. Methodology follows Chapter 2. The chapter is divided into three major sections. Firstly, Section 5.1 comments on SFA and DEA results without inefficiency determinants. Results obtained from each method are discussed and consequently compared across techniques. Secondly, in Section 5.2 efficiency results from SFA with inefficiency determinants included into the mean of the truncated normal distribution of inefficiency are described. At the same time, these are compared to the SFA and DEA efficiency results from Section 5.1. Section 5.3 discusses results for individual hospitals picking up the most interesting observations.

Coelli (1996a;b)'s softwares were used for the estimation. SFA was estimated with FRONTIER 4.1 and DEA models were estimated with DEAP 2.1.

5.1 Results - without Determinants

5.1.1 SFA

Comparing Translog and Cobb-Douglas specifications, the results reveal that the Translog model suffers from overspecification due to its cross product terms. When all 14 explanatory variables were used in the Translog specification, not only were most of the additional variables not significant, but the significance of the original variables worsened.[1] Furthermore, the log likelihood function

[1] Significance worsened primarily for doctor_bed and nurse_bed. The former was significant at 5% and the latter at 1 % significance level in the Cobb-Douglas specification, but both lost all the significance under Translog. The remaining two variables significant under Cobb-

under Cobb-Douglas specification was higher.

Therefore, only Cobb-Douglas specification was applied. To remind, the model further assumed time-variant truncated-normally distributed inefficiency term (with non-zero mean). The theoretical function to be estimated from Equation 2.7 takes the following form:

$$\begin{aligned} \ln(\text{costs}_{it}) &= \beta_0 + \beta_1 \ln(\text{sum\_3\_days}_{it}) + \beta_2 \ln(\text{nursing\_days}_{it}) + \\ &\quad + \beta_3 \ln(\text{doctor\_bed}_{it}) + \beta_4 \ln(\text{nurse\_bed}_{it}) + v_{it} + u_{it} \end{aligned} \tag{5.1}$$

Regression results are provided in Table 5.1. Under Cobb-Douglas specification all of the output variables considered proved significant. Except for nursing days, all have positive signs. Furthermore, the highest elasticity of the sum of non-operating, operating and intensive days is not surprising since they are assumed to be enormously resource demanding areas of hospital care. The negative sign with nursing days was not expected, however. It is believed that there might be a hidden effect of size since big hospitals tend to have nursing wards separated from the hospital itself. They thus have separate accounting and management, and nursing days are thus not included in the analysis out of methodological reasons. Assuming that big hospital have higher costs and no nursing days integrated into the analysis, being a smaller hospital with some nursing days immediately suggest that nursing days decrease costs.

The likelihood ratio test on one-sided error term, which has a mixed χ^2 distribution with three degrees of freedom, reveals that the difference between using a one-sided error term or excluding it is extremely statistically significant. The inclusion of the inefficiency term into the model is thus appropriate. Moreover, the value of the variance of the inefficiency term is quite large in relation to the variance of the composed error as revealed by the γ parameter. Statistical noise thus accounts only for a small portion of the total error variance. Parameter η is negative, significant but of small value which indicates that inefficiency slightly increases over time.

Douglas specification, i.e. sum_3_days and nursing_days stayed so also under the Translog functional form.

Table 5.1: MLE Results - SFA

	coefficient	standard-error	t-ratio	
β_0	12.610	0.4443	28.39	***
sum_3_days	0.5405	0.0422	12.82	***
nursing_days	-0.0147	0.0074	-1.993	**
doctor_bed	0.0891	0.0397	2.245	**
nurse_bed	0.1440	0.0747	1.927	*
σ^2	0.2455	0.0160	15.45	***
γ	0.9446	0.0072	132.1	***
μ	0.9631	0.0818	11.78	***
η	-0.0188	0.0027	-6.935	***
log likelihood function			222.6	
LR one-sided error			644.3	***

Note: *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Estimation of a cost function with FRONTIER 4.1 gives individual Shephard efficiency measures[2] which fall between 1 and infinity. The efficiency scores produced by FRONTIER 4.1 are obtained as:

$$\mathrm{EFF}_i = \frac{E(X_i|u_i, \mathbf{Y}_i)}{E(X_i|u_i = 0, \mathbf{Y}_i)} \tag{5.2}$$

where X_i is the cost of the i-th DMU, $i \in N$. $\mathbf{Y}_i$ represents a vector of outputs of the i-th observation and u_i represents its inefficiency.

Shephard efficiency measures were inverted into Farrell's efficiency resulting in $0 < \frac{1}{\mathrm{EFF}_i} < 1$ for easier interpretation and comparison with the DEA results.[3] Individual efficiency scores are provided in Table A.7. The interpretation the individual scores is such that when a hospital reaches the efficiency score of 0.8, it employs total costs which are 25 % higher than what it would have been were it frontier efficient. In other words, there is a scope for efficiency improvement reaching 20 percentage points.

Frequency plot of average efficiency scores is provided in Figure 5.1. Depicting frequency plots for individual years would not provide much additional information since they reveal a very similar structure. Efficiency scores decrease only slightly over-time which can be concluded after a closer scrutiny of Table A.7. This phenomenon is further supported by a small but negative η coefficient in Table 5.1 as already pointed out. Figure 5.1 suggests that mean efficiency is

[2]The concept was introduced by Shephard (1953).

[3]The relationships between Shephard's and Farrell's concepts of efficiency is discussed in Charnes *et al.* (1978).

around 0.4. It is also visible that the deviation from the mean is quite high reaching 0.20. In addition, Table 5.2, which provides summary statistics for efficiency scores by year, reveals that there was not a single fully efficient observation in any cross section.

Figure 5.1: Frequency Plot - SFA without Determinants Scores

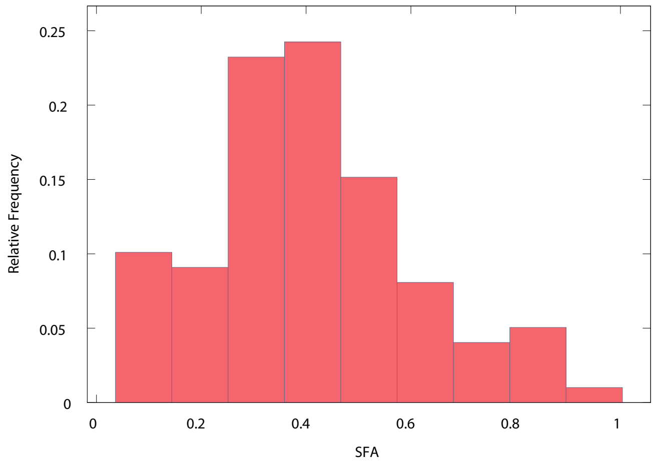


Table 5.2: Summary Statistics - SFA Whole Sample

	2001	2002	2003	2004	2005	2006	2007	2008
mean	0.419	0.410	0.402	0.400	0.394	0.395	0.383	0.376
min	0.104	0.100	0.096	0.092	0.088	0.084	0.080	0.076
max	0.897	0.895	0.893	0.952	0.951	0.950	0.949	0.948
no. obs.	76	82	79	84	84	90	78	88
st.dev.	0.182	0.179	0.176	0.191	0.200	0.198	0.206	0.195

To provide a straightforward comparison of hospitals as far as their efficiencies are concerned, they were ranked such that the highest rank (rank 1) was assigned to the most efficient hospital. Table A.7 shows also these rankings. When analyzing the results for individual hospitals, one can see that rankings of hospitals are considerably stable over-time. In addition to the visual analysis of Table A.7, Spearman's rank correlation was calculated to obtain the intertemporal correlation coefficients. It was calculated using the formula as developed by Spearman (1904):

$$\rho = 1 - \frac{6 \times \sum d^2}{n(n^2-1)} \tag{5.3}$$

$$\rho \in \langle -1, 1 \rangle$$

where d stands for the difference in the ranks and n is the number of pairs compared.

Results for Spearman's Rank Correlation Coefficients for SFA were very significant reaching nearly unity, which suggests stability of rankings over time.

To analyze individual efficiency scores, hospitals were divided into groups as of the division for size dummies proposed in Chapter 3. Group affiliation is thus also included in Table A.7. In addition, summary statistics for size groups is provided in Table 5.3.

Table 5.3: Summary Statistics SFA Groups

≤ 10,000 - Size Group 1								
	2001	2002	2003	2004	2005	2006	2007	2008
mean	0.585	0.573	0.564	0.574	0.581	0.575	0.572	0.556
min	0.409	0.402	0.395	0.388	0.381	0.374	0.367	0.360
max	0.814	0.893	0.891	0.952	0.951	0.950	0.949	0.948
no. obs.	23	25	22	27	27	30	26	28
st.dev.	0.109	0.116	0.118	0.141	0.155	0.155	0.161	0.151
10,001–20,000 - Size Group 2								
	2001	2002	2003	2004	2005	2006	2007	2007
mean	0.443	0.429	0.427	0.411	0.392	0.393	0.378	0.377
min	0.104	0.100	0.096	0.092	0.088	0.084	0.080	0.076
max	0.897	0.895	0.893	0.891	0.889	0.887	0.885	0.883
no. obs.	27	27	28	26	27	29	24	29
st.dev.	0.158	0.159	0.159	0.161	0.166	0.155	0.174	0.163
> 20,001 - Size Group 3								
	2001	2002	2003	2004	2005	2006	2007	2008
mean	0.248	0.255	0.254	0.239	0.228	0.222	0.213	0.213
min	0.121	0.116	0.112	0.107	0.103	0.098	0.094	0.090
max	0.411	0.404	0.398	0.391	0.379	0.372	0.370	0.363
no. obs.	26	30	29	31	30	31	28	31
st.dev.	0.082	0.082	0.085	0.087	0.083	0.081	0.082	0.083

Looking at the standard deviation, it is smaller when hospitals are divided into groups than for the overall sample. It suggests that the division was reasonable revealing a considerable homogeneity of hospitals within groups. It is further apparent that average efficiency decreases as group size increases, being around 0.55 for all years for group 1, i.e. the group consisting of the smallest hospitals; it falls to around 0.4 for group 2 and decreases rapidly for all years for group 3. The average for the whole sample lies slightly below 0.4 as already pointed out above. Large hospitals are thus believed to exert decreasing returns to scale production technology. When size variables are included as determinants of inefficiency into the model, inefficiency of this group is expected to decrease considerably.

Furthermore, the highest stability of efficiency scores over-time is in the group of the smallest hospitals while a remarkable intertemporal decrease in efficiency scores takes place in group 3. The efficiency scores are however quite low in absolute terms regardless of size of the hospital. Inclusion of determinants of inefficiency is thus likely to have an effect in general.

5.1.2 DEA

For the DEA analysis, the same input and outputs as in the SFA were used. Even though DEA can handle multicollinearity of outputs which was found with "total empty bed days" towards patient days, output variables were adjusted in the same way as for SFA purposes in order for the comparison of the results to be possible. However, since DEA does not require any assumption on the cost function, inputs and outputs in natural units were used. Table A.8 and Table A.9 depict Farrell's efficiency scores for DEA CRS and DEA VRS assumptions, respectively. The interpretation of the efficiency scores is the same as in Subsection 5.1.1, i.e. the higher the efficiency score, the closer the hospital is to the efficiency frontier.

As already pointed out in Chapter 2, there are more fully efficient DMUs under VRS than under CRS since VRS envelopes the data more tightly. Indeed, summary statistics for the whole sample under CRS and VRS assumption in Table 5.4 for each cross-section reveals that the number of fully efficient observations under VRS is considerably higher than under CRS. Under VRS, observations of specific size do not have comparable observations and thus become automatically efficient. Average efficiency for all 99 hospital in all years reaches 0.8 for VRS but only around 0.55 for CRS.

As is shown in Table 5.4, year 2006 reveals very different efficiency scores from the remaining cross-sections. In overall, the efficiency scores are much lower compared to other years both from CRS and VRS perspectives. Furthermore, a thorough analysis of the effects on individual efficiency scores in Table A.8 and Table A.9 suggests that hospitals affected under CRS were most likely to be influenced under VRS as well.

The enormous decrease in efficiency scores in 2006 is expected to have been

Table 5.4: Summary Statistics - DEA Whole Sample

	2001		2002		2003		2004	
	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
	CRS01	VRS01	CRS02	VRS02	CRS03	VRS03	CRS04	VRS04
mean	0.545	0.837	0.587	0.798	0.575	0.829	0.569	0.860
min	0.114	0.463	0.132	0.428	0.110	0.465	0.100	0.504
max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
st.dev.	0.182	0.146	0.203	0.181	0.190	0.157	0.199	0.143
no. obs.	76	76	82	82	79	79	84	84
no. efficient	5	24	6	21	5	25	7	27

	2005		2006		2007		2008	
	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
mean	0.558	0.839	0.331	0.507	0.553	0.795	0.571	0.859
min	0.087	0.387	0.042	0.061	0.096	0.410	0.154	0.511
max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
st.dev.	0.201	0.168	0.243	0.325	0.206	0.179	0.208	0.151
no. obs.	84	84	90	90	78	78	88	88
no. efficient	7	27	5	18	7	25	6	34

caused by some uncovered common noise effect, since no such change happened when SFA efficiency was estimated. Furthermore, efficiency scores in SFA are higher since the method can distinguish between inefficiency and white noise. DEA considers the entire deviation to be inefficiency, thus its efficiency scores are lower as visible from the comparison of summary statistics for the entire sample in Table 5.4 and Table 5.2. Some portion of the noise may be attributed to the process of transformation from public for-profit to public not-for-profit hospitals which to a large extent took place in 2006. Specifically 23 out of 41 hospitals which were transformed during the period examined changed their status in 2006.[4] Nevertheless a closer scrutiny of the intertemporal changes in costs and input/output ratios suggest that primarily for-profit public hospitals increased both their costs and input/output ratios remarkably in 2006. Both in preceding and subsequent years, the ratios changed by quite low amount. The noise may thus rather be caused by inconsistent political decisions.

Again, similar to SFA results, efficiencies of individual hospitals were ranked relative to the rest of the group. To find out stability of CRS and VRS rankings, Spearman's Rank Correlation coefficients were calculated using the same formula as in the previous section. However, Spearman's Rank Correlation Coefficients unfortunately suffer from an important imperfection when there are more hospitals of the same efficiency scores in one of the cross-sections

[4]The effect the process of transformation on efficiency scores is however not subject of this analysis. It can thus serve as a recommendation for further research.

examined. Specifically, when there are more fully efficient observations, all are ranked the same. The second most efficient hospital then gets a rank depending on how many fully efficient observations there are. Spearman's Rank Correlation Coefficient obtains the rank of the equally efficient observations by averaging the ranks which otherwise would be the case. For example, the rank for 10 hospitals which are fully efficient is calculated as:

$$\frac{\sum_{r=1}^{10} r}{10} \tag{5.4}$$

where r stands for rank.

All 10 fully efficient hospitals would thus be assigned rank 5.5. instead of 1. The consequence is a much lower correlation coefficient between the years concerned when there are different numbers of fully efficient observations.

DEA CRS full Spearman's Rank Correlation matrix is provided in Table 5.5 even though only two subsequent years are of primary interest. Table 5.5 reveals that correlation between ranks is quite high, for some years reaching up to 0.9. VRS correlations coefficients in Table 5.6 are somewhat lower. The high correlation among cross–section in CRS is explained by the stable size of hospitals. Since under CRS big hospitals are always inefficient, correlation of intertemporal efficiency rankings and thus its stability is higher under CRS than under VRS. Nevertheless, correlations both for DEA CRS and DEA VRS are significant which suggests intertemporal stability of rankings under both methods, even though not as high as under SFA which considers major efficiency deviations as errors. Correlation for year 2006 is again an exception revealing much lower correlation with immediately preceding and subsequent years in terms of efficiency rankings.

Table 5.5: Spearman's Rank Correlation Coefficient - CRS

	2001	2002	2003	2004	2005	2006	2007	2008
2001	1							
2002	0.901	1						
2003	0.840	0.897	1					
2004	0.806	0.814	0.928	1				
2005	0.771	0.800	0.881	0.913	1			
2006	0.734	0.746	0.754	0.783	0.777	1		
2007	0.721	0.653	0.765	0.798	0.867	0.763	1	
2008	0.774	0.728	0.788	0.832	0.884	0.843	0.902	1

Note: All coefficients were significant at 1 % level.

Table 5.6: Spearman's Rank Correlation Coefficient - VRS

	2001	2002	2003	2004	2005	2006	2007	2008
2001	1							
2002	0.649	1						
2003	0.510	0.660	1					
2004	0.461	0.578	0.602	1				
2005	0.416	0.530	0.602	0.833	1			
2006	0.397	0.530	0.605	0.445	0.311	1		
2007	0.282	0.303	0.324	0.438	0.547	0.445	1	
2008	0.357	0.305	0.363	0.392	0.494	0.301	0.631	1

Note: All coefficients were significant at 1 % level.

Consequently, Spearman's Rank Correlation Coefficients between DEA CRS and DEA VRS were calculated for individual years. The correlation of ranks is highly appropriate particularly when there are different distributions of variables, i.e. across methods. Correlation coefficients for CRS and VRS ranks in respective years are provided in Table 5.7. Correlation of around 0.3 was present for all years except for 2006 when the correlation was significantly higher. In 2006, primarily big hospitals had higher costs (and lower average efficiency) as visible from Table 5.8. Notwithstanding, some big hospitals stayed on the frontier since maximum efficiency in group 3 was still 1.00 under VRS. In other words, some big hospitals stayed on the frontier but others moved further away and thus their ranking worsened. Under CRS these big hospitals were always far away from the frontier. Thus rank correlation between DEA CRS and DEA VRS increases in 2006.

Table 5.7: DEA CRS vs. DEA VRS Spearman's Rank Correlations

Year	Coefficient
2001	0.283
2002	0.274
2003	0.324
2004	0.350
2005	0.254
2006	0.658
2007	0.386
2008	0.398

Note: All coefficients were significant at 1 % level.

The sample was, as previously, analyzed in division into size groups. Summary statistics for individual groups is provided in Table 5.8. Standard deviation of efficiency scores for the entire sample is again greater than standard deviation for disaggregated groups when Table 5.4 and Table 5.8 are compared. It is thus again reasonable to analyze the size groups separately. On average, the smaller

Table 5.8: Summary Statistics - DEA Groups

≤ 10,000 - Size Group 1								
	2001		2002		2003		2004	
	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
mean	0.689	0.839	0.767	0.850	0.737	0.841	0.713	0.872
min	0.467	0.603	0.503	0.522	0.475	0.476	0.41	0.504
max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
st.dev.	0.163	0.139	0.158	0.143	0.168	0.160	0.185	0.138
no. obs.	23	23	25	25	22	22	27	27
no. efficient	4	8	5	7	4	8	5	10
	2005		2006		2007		2008	
	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
mean	0.701	0.800	0.581	0.723	0.699	0.801	0.757	0.865
min	0.387	0.387	0.253	0.32	0.349	0.434	0.404	0.511
max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
st.dev.	0.190	0.182	0.235	0.235	0.198	0.195	0.180	0.152
no. obs.	27	27	30	30	26	26	28	28
no. efficient	6	9	5	8	6	11	5	10
10,001–20,000 - Size Group 2								
	2001		2002		2003		2004	
	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
mean	0.541	0.813	0.564	0.727	0.573	0.783	0.564	0.822
min	0.114	0.463	0.132	0.428	0.11	0.465	0.1	0.515
max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
st.dev.	0.170	0.159	0.174	0.198	0.169	0.177	0.178	0.163
no. obs.	27	27	27	27	28	28	26	26
no. efficient	1	7	1	7	1	9	2	8
	2005		2006		2007		2008	
	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
mean	0.548	0.800	0.284	0.467	0.539	0.789	0.552	0.837
min	0.087	0.471	0.069	0.161	0.096	0.41	0.154	0.528
max	1.000	1.000	0.593	1.000	1.000	1.000	1.000	1.000
st.dev.	0.182	0.173	0.111	0.283	0.181	0.190	0.166	0.165
no. obs.	27	27	29	29	24	24	29	29
no. efficient	1	5	0	5	1	7	1	12
> 20,001 - Size Group 3								
	2001		2002		2003		2004	
	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
mean	0.422	0.861	0.457	0.818	0.454	0.865	0.447	0.881
min	0.259	0.631	0.24	0.451	0.24	0.541	0.203	0.591
max	0.608	1.000	0.916	1.000	0.651	1.000	0.699	1.000
st.dev.	0.099	0.134	0.144	0.175	0.124	0.120	0.132	0.119
no. obs.	26	26	30	30	29	29	31	31
no. efficient	0	9	0	7	0	8	0	9
	2005		2006		2007		2008	
	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
mean	0.437	0.910	0.132	0.335	0.429	0.793	0.422	0.875
min	0.207	0.618	0.042	0.061	0.212	0.534	0.221	0.636
max	0.671	1.000	0.294	1.000	0.791	1.000	0.662	1.000
st.dev.	0.133	0.120	0.066	0.318	0.138	0.152	0.120	0.133
no. obs.	30	30	31	31	28	28	31	31
no. efficient	0	13	0	5	0	7	0	12

the hospital, the lower the difference between CRS and VRS. In other words, for smaller hospitals the frontier point under CRS and VRS is very similar. Specifically, for group 1, CRS scores are around 0.7 and VRS around 0.85 on average while for group 3 CRS is around 0.4 on average and VRS score increases up to 0.9.[5] Moreover, bigger hospitals have only a few or even none efficient hospitals under CRS. The number of fully efficient hospitals for all groups is approximately equal under VRS. Keeping in mind that all groups are of the same size as to the number of observations, the number of efficient hospitals in each groups is quite a good means for comparison.

As already pointed out, year 2006 is very special. It thus deserves further attention also at the disaggregated level. The difference between the scores in 2006, both for VRS and CRS, and the immediately preceding and subsequent years is much larger than when other neighboring cross sections are analyzed similarly. Furthermore, as hospital size increases, the difference becomes greater, particularly for VRS results.

DEA with Technological Indices

An additional analysis with technological indices as output variables was carried out. Due to data availability, only 2004 cross section was analyzed. However, not all hospitals included in 2004 cross-section were provided with the data to calculate technological indices. Two technological indices were included, i.e. equipment per 10,000 patients and procedures per patients.[6]

By adding new output variables, the dimension increases and thus the number of fully efficient observations as well as the mean efficiency increase. Under CRS the number of fully efficient observation increased by 3, under VRS by 8 observations. Individual efficiency scores for the entire sample, as well as their rankings are provided in Table A.10.

The results further reveal that the additional output dimensions, represented by the two technology indices, did not shift the overall frontier but rather had only an effect on the hospitals which were provided with the data on technology. As a consequence, average efficiency of the entire sample increased slightly both for

[5] Year 2006 is again an exception.

[6] Specifically, the 2004 cross-section included 84 hospitals in total, 70 of which were provided with the technological index on equipment and 65 hospitals were analyzed with the technology index on procedures.

Table 5.9: Summary Statistics - DEA With and Without TI

	CRS04	VRS04	CRS04_TI	VRS04_TI
mean	0.569	0.860	0.607	0.889
min	0.100	0.504	0.140	0.504
max	1	1	1	1
st.dev.	0.199	0.143	0.223	0.137
no. obs.	84	84	84	84
no. efficient	7	27	10	35

VRS and CRS as obvious from Table 5.9. However, efficiency scores of hospitals which were provided with the data only on one or even no technological index did not change. In other words, had the new output dimension shifted the frontier, the efficiency of hospitals without data on this dimension would have decreased. These conclusions are consistent with Zuckerman *et al.* (1994); Rosko *et al.* (1995) who found out that the inclusion of some quality indicators does not have a great effect on efficiency.

5.1.3 Comparison DEA vs. SFA

Efficiency scores obtained from DEA and SFA without determinants differ which is consistent with Chirikos & Sear (2000). Furthermore, they have different distributions, thus the only means of comparison is correlation of rankings.

Spearman's Rank Correlation Coefficients provided in Table 5.10 reveals that ranks from DEA CRS and SFA are correlated at around 0.8 on average for each year. It suggests that the results are qualitatively similar. On the other hand, it is visible in Table 5.11 that the correlation between VRS and SFA ranks is insignificant, except for 2006. It has to be kept in mind in this context that there is primarily a technical problem in the comparison of ranks between DEA VRS and SFA, i.e. similar to comparing DEA VRS and DEA CRS. For the purposes of Spearman's Rank Correlation Coefficient, ranks are calculated such that the ranks which otherwise would be applicable are averaged for the DMUs with the same scores. All these DMUs are assigned the obtained rank. In other words, since quite a large number of hospitals becomes newly efficient under VRS, it is very difficult to compare VRS ranks to those obtained under SFA where there is not a single fully efficient observation.

Even though it is inappropriate to compare efficiency scores across different methods, valuable information can be retrieved from the frequency structure

Table 5.10: DEA CRS vs. SFA Spearman's Rank Correlations

Year	Coefficient
2001	0.822
2002	0.831
2003	0.837
2004	0.809
2005	0.833
2006	0.896
2007	0.796
2008	0.889

Note: All coefficients were significant at 1 % level.

Table 5.11: DEA VRS vs. SFA Spearman's Rank Correlations

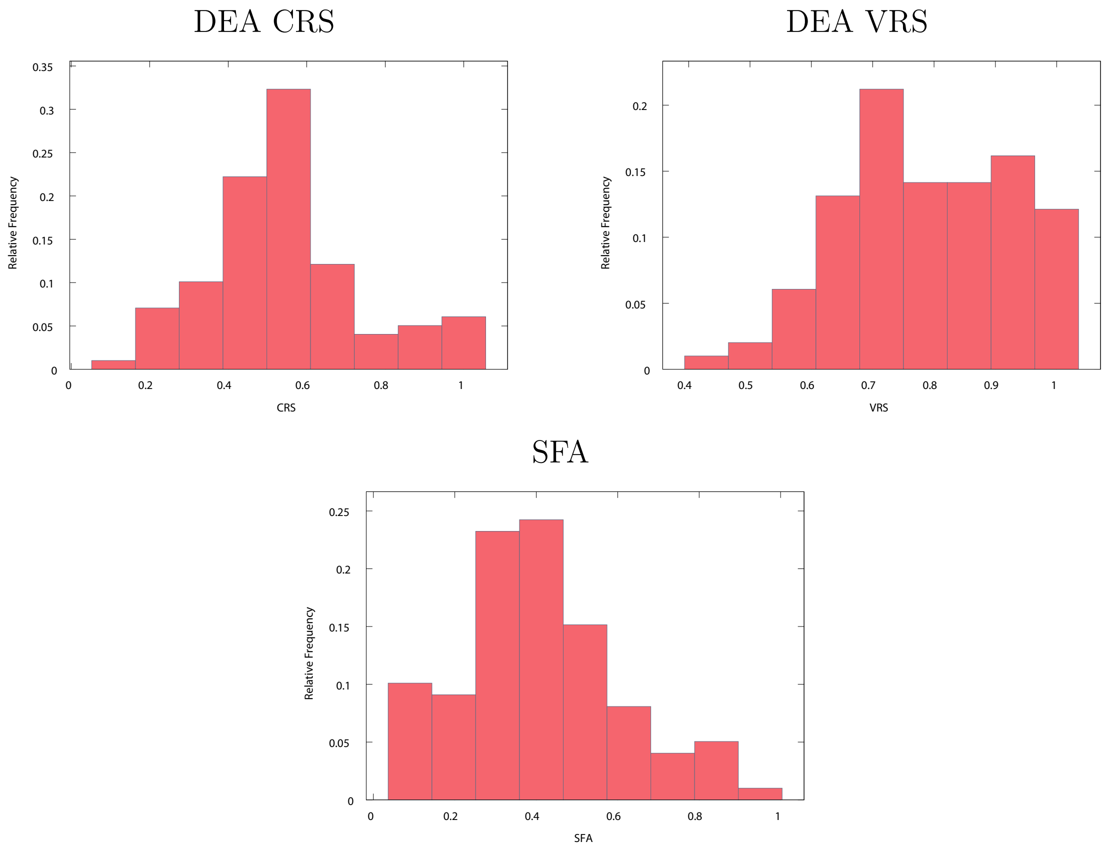
Year	Coefficient	
2001	-0.049	
2002	-0.016	
2003	-0.038	
2004	0.098	
2005	-0.061	
2006	0.404	***
2007	0.139	
2008	0.169	

Note: *** denote significance at 1 % level. The remaining coefficients were not significant even at 10 % level.

of the different sets of efficiency scores. Frequency plots of efficiency scores averaged over the period of 2001–2008 for DEA CRS, DEA VRS and SFA are depicted in Figure 5.2. Comparing DEA CRS and SFA, one recognizes that DEA CRS scores are on average higher and with more fully efficient observations than those obtained under SFA. SFA has, on the other hand, more observations to the left tail of the efficiency distribution. However, one can still recognize that their structures is to some extent similar. Table 5.10 and Figure 5.2 point out at the same phenomena. The analysis of DEA VRS efficiency distribution in Figure 5.2 confirms that DEA VRS results are confounded by the effect of many efficient observations due to the returns to the scale assumption.

In spite of the problematic comparison of rankings among different methods due to the above stated reasons, Chirikos & Sear (2000) discovered that various methods tend to classify observations in the top and bottom quantile of the efficiency distribution similarly. Therefore, sets of average efficiency scores

Figure 5.2: Frequency Plot - SFA, DEA CRS and DEA VRS Scores



obtained from each method were thoroughly analyzed. Summary statistics is provided in Table 5.12. Individual average efficiency scores and rankings are provided in Table A.11.

Table 5.12: Summary Statistics - Average Efficiency Scores

	CRS	VRS	SFA
mean	0.541	0.788	0.410
min	0.108	0.429	0.090
max	1.000	1.000	0.950
st.dev.	0.195	0.138	0.197
no. obs.	99	99	99
no. efficient	5	9	0

Following the rationale of Chirikos & Sear (2000), top and bottom deciles from all sets were determined, each obtaining 10 hospitals. Hospitals classified in these deciles were assigned a respective rank. A list of hospitals classified in top and bottom deciles under DEA CRS, DEA VRS and SFA is provided in

Table 5.13. These ranks were consequently compared using Spearman's Rank Correlation Coefficients. Results of this analysis are provided in Table 5.14.

Table 5.13 reveals that top deciles of DEA CRS and DEA VRS contain a lot of identical observations, specifically hospitals 12, 29, 34, 52, 85, 63, 40. Except for the two last mentioned, all are fully efficient over the entire period under both specifications and at the same time represent all fully efficient observations under CRS. It is also important to point out that the observations in the bottom deciles differ. However, the bottom decile of DEA CRS specification contains observations 25 and 90 which move to the top decile under VRS. It suggests that these two hospitals do not have many comparable observations. Indeed, hospital 25 belongs to the two largest hospitals in the sample. On the other hand, observation 90 is very special in terms of the quality of care provided (on average, one nurse takes care of only 1.3 patients per day). When DEA CRS and SFA deciles are compared one recognizes a considerable similarity. Specifically, there are only 2 different hospitals among the top ten observations, the same applies to the bottom decile. Furthermore, observations 25 and 90 are classified in the bottom quantile of SFA. Having just classified hospitals 25 in the bottom quantile of DEA CRS and the top one of DEA VRS, SFA is thus likely to reflect rather constant returns to scale.

Table 5.13: Hospitals in Top & Bottom Deciles, without Determinants

CRS		VRS		SFA	
top decile	bottom decile	top decile	bottom decile	top decile	bottom decile
12	94	12	86	34	93
29	25	29	6	24	64
34	64	34	3	40	54
52	54	52	45	12	88
85	91	85	39	14	35
63	93	40	79	85	8
14	8	18	58	83	91
24	35	25	26	13	25
13	23	90	93	70	23
40	90	63	97	63	90

Note: Hospitals are ordered from the most to the least efficient ones in each column.

Spearman's Rank Correlation Coefficients for top and bottom deciles of different models proved significant in all circumstances. The findings of this thesis thus confirm results of Chirikos & Sear (2000) who compared results obtained under different methods. In other words, DEA CRS, DEA VRS and SFA without determinants tend to classify the most and the least efficient observations in the sample to a certain degree consistently.

Table 5.14: Spearman's Rank Correlations
- Top & Bottom Deciles, without Determinants

	CRS	VRS	SFA
CRS	1		
VRS	0.903	1	
SFA	0.826	0.691 *	1

Note: * significant at 10 % level, otherwise significant at 1 % level.

Results for year 2006 deserve particular attention again. Just to remind, DEA CRS and SFA rankings and DEA VRS and SFA rankings for 2006 are both significantly correlated as obvious from Table 5.10 and Table 5.11. It is worth pointing out that the change in efficiency scores compared to previous and subsequent years under SFA was found to be consistent with the analysis for the remaining years. This is however, not the case with DEA VRS and DEA CRS results as Table 5.5 and Table 5.6 suggest. It is thus indeed believed that some white noise resulting maybe from inconsistent policy, transformation of hospitals into joint-stock companies or even from some other spheres, was captured by SFA but was considered as inefficiency by DEA, for DEA is unable to account for the unexplained noise.

When determinants of efficiency are taken into consideration, efficiency scores for SFA are likely to substantially increase. In the following section determinants of efficiency will be included into the mean of the inefficiency term in the SFA model, following methodology explained in Chapter 2.

5.2 Results - with Determinants

As already pointed out in Chapter 2, SFA is highly appropriate for the inclusion of determinants into the mean.[7] The second model defined in Chapter 2 in 2.9 will be used. In other words, the effect of determinants of inefficiency will be estimated jointly with the frontier estimation. No two-step analysis of the efficiency scores is thus needed, which represents a major advantage of this method - the inefficiency terms are not serially correlated as in a two step estimation.

In what follows, first the model specification will be outlined, consequently the effect of each variable obtained from the regression will be discussed. Lastly, efficiency scores for individual hospitals will be analyzed and compared to the previous results.

The frontier regression looks as when no determinants were included in Equation 5.1. But the inefficiency term takes the following form:

$$\begin{aligned} u_{it} &= \delta_0 + \delta_1 \text{teaching} + \delta_2 \text{size1} + \delta_3 \text{size3} + \\ &\quad + \delta_4 \text{not\_profit} + \delta_5 \text{population} + \delta_6 \text{over\_65} + \delta_7 \text{unempl} + \\ &\quad + \delta_8 \text{salary} + \delta_9 \text{ competition} + w_{it} \end{aligned} \tag{5.5}$$

Results of the Maximum Likelihood Estimation is provided in Table 5.15. As in the case of the regression without determinants, all variables of the stochastic frontier regression proved significant. This time, however, also coefficient for nursing days is positive and thus consistent with the initial expectations. It is thus believed that the hypothesis about some hidden effect in the output variable 'nursing days' in the results of the MLE regression without determinants in Table 5.1 was reasonable. Of all the output variables, the highest elasticity was for the sum of non-operative, operative and intensive care days, which is consistent with Table 5.1. The sum of coefficients for output variables is bigger than one. Since axes are reversed in the input orientation (input–output), decreasing returns to scale are present.

The likelihood ratio test on one-sided error term, i.e. the test on the presence of the inefficiency term, is significant suggesting that the inefficiency term is highly appropriate in the analysis. Parameter γ is also significant but smaller

[7]As suggested in Section 2.2 a non-zero mean and thus truncated normal distribution is a prerequisite.

than in the analysis without determinants. It means that the variance of the inefficiency term takes up a much smaller part of the total variance than before. In other words, compared to the previous regression, more of the total variance of the error term is now captured by the variance of the white noise rather than inefficiency since a certain portion of inefficiency was explained by determinants and thus is smaller than before.

Table 5.15: MLE Results
- SFA with Determinants

	coefficient	standard error	t-ratio	
β_0	10.5100	0.32150	32.69	***
sum_3_days	0.86480	0.02861	30.23	***
nursing_days	0.01692	0.00236	7.165	***
doctor_bed	0.41780	0.05405	7.729	***
nurse_bed	0.57370	0.08147	7.042	***
δ_0	-0.45320	0.14770	-3.068	***
teaching	0.35590	0.04885	7.285	***
size1	-0.39150	0.05202	-7.526	***
size3	0.08703	0.04014	2.168	***
not_profit	0.13140	0.04341	3.027	***
population	-3.694E-07	1.684E-07	-2.193	***
over_65	0.00653	0.00498	1.314	†
unempl	-0.00730	0.00442	-1.652	*
salary	3.445E-05	8.903E-06	3.869	***
competition	-0.00545	0.00299	-1.824	*
σ^2	0.06471	0.00380	17.00	***
γ	0.08799	0.00395	2.230	**
log likelihood function			-22.89	
LR one-sided error			153.3	

Note: *** denotes significance at 1% level, ** significance at 5% level, * significance at 10% level, † one-tail significance at 10% level.

All determinants of inefficiency proved significant, however the share of the elderly was significant at one-tail distribution only. In other words, we reject the null hypothesis of the negative effect of the share of the elderly on inefficiency with the probability of 90 %.

Teaching status has a positive effect on inefficiency as expected, moreover, its coefficient is the largest of all the determinants. The result thus confirms that teaching hospitals are very special in their nature. They incur specific costs connected with teaching material, facility or personnel.

Both dummy variables reflecting the effect of size on inefficiency are strongly significant even at 1 % level. The sign of their coefficients further indicates that being a very small hospital decreases inefficiency and being very big has a positive effect of inefficiency, even though by quite a small amount. The results suggest that there are decreasing returns to scale present in the production technology of hospitals and thus being of a certain size should explain some portion of inefficiency.

Not-for-profit ownership proved to significantly increase inefficiency. The result is consistent with the initial hypothesis keeping in mind that the purpose of transformation into joint-stock companies was to curb extensive costs and inefficiency.

The effect of the size of the population in municipalities proved significant. Nevertheless, with opposite sign than expected, i.e. the coefficient for this variable is negative.[8] Population size may contain a number of effects. The occupancy rate may be higher in bigger cities and thus hospitals demonstrate more patient days. At the same time, the quality effect which decreases because of higher occupancy rate (medical staff does not have so much time for each patient, patients do not have separate rooms) may increase through the availability of better medical equipment and more advanced, effective and less costly means of treatment.

The higher the share of the elderly, the higher the inefficiency of hospitals as expected. The coefficient proved significant at 10 % at one tail distribution. The hypothesis of the negative effect is significantly rejected. It is consistent with the findings of Frohloff (2007) who concluded that a large share of the elderly increases inefficiency of hospitals considerably.

The significant effect of unemployment rate on the efficiency of hospitals suggests that higher unemployment rate in districts of municipalities with extended powers decreases inefficiency of hospitals in the respective cities. The explanation thus could follow the above stated notion that when unemployment rate is high, there are higher opportunity costs of not working and thus the people are more interested in taking precautionary measures to avoid long-term and costly medical treatment in hospitals.

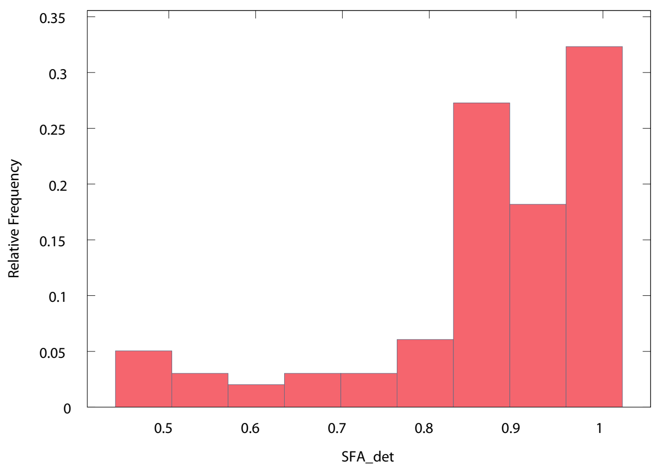
The effect of salary in districts is positive and significant suggesting that as wages increase, inefficiency increases too. Average salary in the area is a proxy

[8] The size of the coefficient is very small, nevertheless, determinants of inefficiency are included in absolute numbers. Therefore, the effect of the size of population is not that small as it might seem at first sight.

for salaries of medical personnel. Therefore, as wages increase, so do costs and consequently inefficiency of hospitals.[9]

The sign of the coefficient for the number of hospitals in the region is negative which is consistent with the initial assumption that competition exerts pressures to decrease inefficiency. The same result concerning the sign of the coefficient was reached by Zuckerman *et al.* (1994) who measured efficiency of hospitals in the U.S.A., however their coefficient proved insignificant.[10]

Figure 5.3: Frequency Plot - SFA with Determinants Scores



Individual efficiency scores (expressed as Farrell's measure) obtained under SFA with determinants are provided in Table A.12.

A frequency plot of efficiency scores of SFA with determinants is depicted in Figure 5.3. As in Section 5.1, individual efficiency scores were averaged cross-sectionally. There is no need to include cross-sectional frequency plots since they were found to be very similar. It can be seen that efficiency of most hospitals is close to one (the figure is skewed to the right), thus inefficiency represents quite a small part. Mean efficiency for the whole sample is around

[9]Salaries of medical staff would have been a better proxy, however, at this point the data was unavailable.

[10]An alternative measure of competition was tested such that the number of hospitals in the region was weighted by the size of the population of respective regions. It was expected that in bigger regions competition among hospitals is less harmful. Weighting by population was assumed to account for this problem. Nevertheless the weighted competition variable proved insignificant. A recommendation for further research is also to test significance of the competition variable which accounts for distances among various municipalities where hospitals are situated. Currently, such an analysis is beyond the scope of this thesis.

Table 5.16: Summary Statistics - SFA with Determinants, Whole Sample

	2001	2002	2003	2004	2005	2006	2007	2008
mean	0.888	0.881	0.866	0.859	0.850	0.851	0.829	0.835
min	0.498	0.516	0.476	0.485	0.474	0.449	0.445	0.440
max	0.991	0.991	0.990	0.990	0.989	0.990	0.987	0.986
st.dev.	0.130	0.125	0.132	0.146	0.152	0.154	0.165	0.160
no. obs.	76	82	79	84	84	90	78	88

0.85. Summary statistics of efficiency scores for the whole sample is provided in Table 5.16. In addition, it reveals that there was again not any fully efficient observation in any cross-section.

In order to find stability of efficiency rankings of SFA with determinants over time, Spearman's Rank Correlation Coefficient was calculated. Results are provided in Table 5.17. From the results revealed in Table 5.17, it can be concluded that rankings of the efficiency scores obtained from SFA with determinants are stable over time, with the correlation coefficient reaching well over 0.9 for the neighboring cross-sections.

Table 5.17: Spearman's Rank Correlation Coefficient - SFA with Determinants

	2001	2002	2003	2004	2005	2006	2007	2008
2001	1							
2002	0.870	1						
2003	0.842	0.990	1					
2004	0.857	0.972	0.979	1				
2005	0.851	0.965	0.973	0.994	1			
2006	0.807	0.917	0.920	0.953	0.968	1		
2007	0.811	0.915	0.906	0.942	0.951	0.985	1	
2008	0.821	0.900	0.891	0.925	0.943	0.976	0.996	1

Note: All coefficients were significant at 1 % level.

Table 5.18 provides summary statistics for size groups. Interestingly, having accounted for size in the regression, differences among groups with respect to the average efficiency pertain, even though decrease considerably compared to the specification without determinants. In other words, efficiency scores for smaller hospitals are still higher than those of bigger hospitals. It is thus expected that big hospitals are either inefficient or rather that there might be omitted variables connected only with bigger hospitals which influence their efficiency. In other words, if these determinants are taken care of, average efficiency of all groups should be approximately equal.

Standard deviation of efficiency scores for groups 1 and 2 are imperceptible, however, that for group 3 is higher than for the sample as a whole. One can

Table 5.18: Summary Statistics - SFA with Determinants, Groups

≤ 10,000 - Size Group 1								
	2001	2002	2003	2004	2005	2006	2007	2008
mean	0.983	0.985	0.983	0.984	0.982	0.981	0.979	0.978
min	0.946	0.966	0.962	0.957	0.951	0.936	0.931	0.920
max	0.991	0.991	0.990	0.990	0.989	0.990	0.987	0.986
st.dev.	0.012	0.005	0.006	0.006	0.007	0.009	0.010	0.012
no. obs.	24	25	22	27	27	30	26	28
10,001–20,000 - Size Group 2								
	2001	2002	2003	2004	2005	2006	2007	2008
mean	0.907	0.908	0.894	0.891	0.875	0.881	0.858	0.863
min	0.682	0.719	0.691	0.669	0.645	0.629	0.619	0.631
max	0.971	0.966	0.957	0.960	0.957	0.952	0.934	0.942
st.dev.	0.061	0.045	0.049	0.057	0.074	0.063	0.079	0.076
no. obs.	27	27	28	26	27	29	24	29
> 20,001 - Size Group 3								
	2001	2002	2003	2004	2005	2006	2007	2008
mean	0.778	0.770	0.751	0.724	0.708	0.696	0.666	0.679
min	0.498	0.516	0.476	0.485	0.474	0.449	0.445	0.440
max	0.988	0.941	0.934	0.918	0.902	0.863	0.838	0.873
st.dev.	0.161	0.138	0.144	0.151	0.152	0.153	0.150	0.153
no. obs.	25	30	29	31	30	31	28	31

thus conclude, that individual efficiencies tend to vary considerably within this group.

Table 5.19 identifies the most and least efficient hospitals under SFA with determinants. A closer scrutiny reveals that hospitals with the highest efficiency scores belong to Group 1 exclusively. On the other hand, the group of the least efficient hospitals is formed by teaching hospitals which belong to Group 3. Furthermore, one should notice that efficiency scores for teaching hospitals are much lower compared even to other hospitals classified in group 3.

5.2.1 Comparison of SFA with Determinants and Previous Results

Looking at the results in Table A.7 and Table A.12, it is obvious that efficiency scores increase markedly when inefficiency determinants are included. It suggests that using determinants is important since otherwise low efficiency scores might be wrongly regarded as inefficiency while instead being caused by various individual-specific characteristics beyond the control of hospitals.

Efficiency scores for SFA with and without determinants were compared in

Table 5.19: Hospitals in Top & Bottom Deciles, with Determinants

top decile	bottom decile
68	25
85	54
50	35
34	8
70	64
71	91
80	89
13	88
49	92
40	94

Note: Efficiency scores were averaged over the period and averaged efficiencies ordered.

Table 5.20: SFA with vs. SFA without Determinants Spearman's Rank Correlations

Year	Coefficient	
	value	rank
2001	0.626	0.779
2002	0.723	0.864
2003	0.726	0.847
2004	0.745	0.878
2005	0.744	0.885
2006	0.728	0.873
2007	0.745	0.877
2008	0.730	0.857

Note: All coefficients are significant at 1 % level.

each cross section. The correlation of values reveal a coefficient of about 0.7. Correlation of ranks in respective years reaches around 0.85 as obvious in Table 5.20. All correlations are significant, however not extremely high. It implies that individual-specific determinants cause asymmetric shifts in the values of efficiency scores and ranks depending on the characteristics of each hospital.

Table 5.21 depicts rank correlation coefficients for DEA CRS and SFA with determinants. Table 5.22 provides rank correlation coefficients for DEA VRS and SFA with determinants.

It is obvious that correlation of ranks decreased when SFA with determinants and DEA CRS were compared as opposed to Table 5.10 when determinants were not included. However, when the rankings of SFA with determinants were compared to DEA VRS, correlation did not increase at all compared to

Table 5.21: DEA CRS vs. SFA with Determinants Spearman's Rank Correlations

Year	Coefficient
2001	0.646
2002	0.796
2003	0.798
2004	0.730
2005	0.723
2006	0.858
2007	0.725
2008	0.762

Note: All coefficients were significant at 1 % level.

the situation without determinants in Table 5.11. The explanation for the low correlation of SFA with determinants and results from previous non-parametric methods stems again from the fact that under SFA with determinants various factors were newly included. They are likely to have caused shifts in efficiency rankings of SFA since the shifts in the efficiency score depend on the characteristics of each hospital. Rank correlations of the top and bottom deciles between SFA with determinants and SFA without determinants, DEA CRS and DEA VRS is only very weakly significant. It thus implies that SFA with determinants indeed represents a different model.

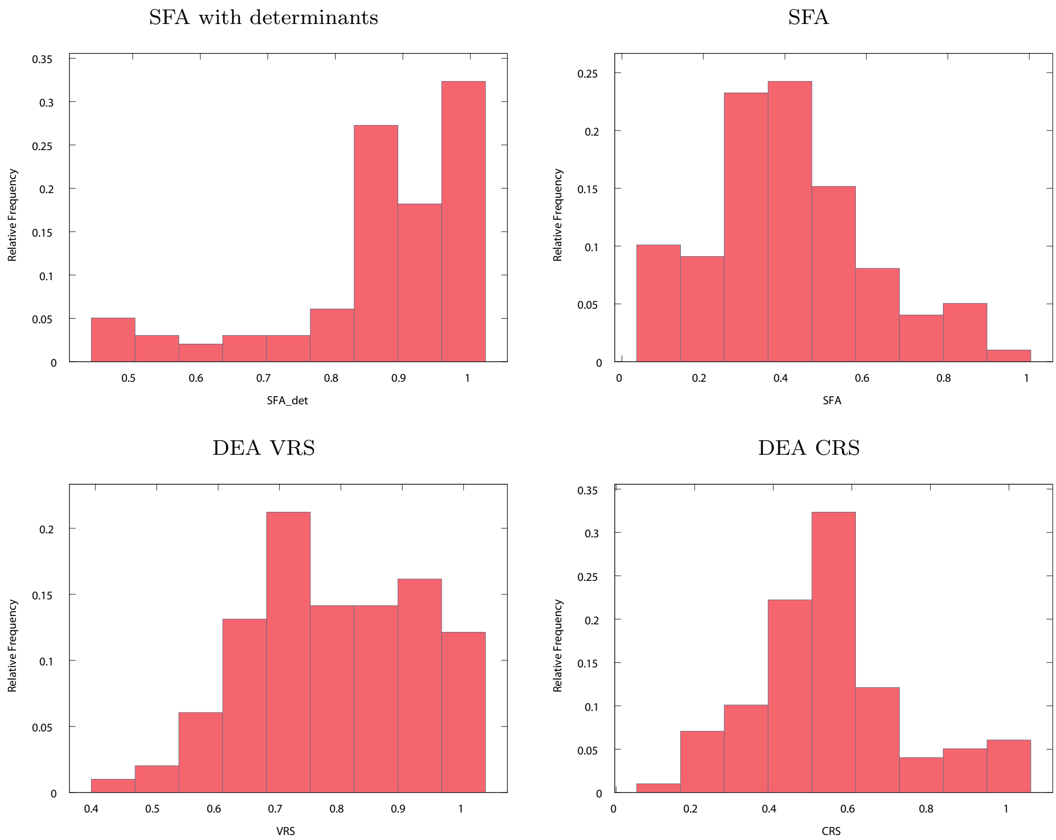
Table 5.22: DEA VRS vs. SFA with Determinants Spearman's Rank Correlations

Year	Coefficient	
2001	-0.047	
2002	0.052	
2003	0.021	
2004	0.106	
2005	-0.100	
2006	0.484	***
2007	0.085	
2008	0.094	

Note: *** significant at 1% level, otherwise insignificant.

Valuable information can again be captured from the frequency structure of the different sets of efficiency scores. Frequency plot for average efficiency scores from each method is depicted in Figure 5.4 Comparing SFA with determinants in to DEA VRS, DEA CRS and SFA without determinants, one notices some similarity between SFA with determinants and DEA VRS frequency plots, rather than between DEA CRS or SFA without determinants and SFA with

Figure 5.4: Frequency Plot
- SFA, DEA CRS, DEA VRS, SFA with Determinants



determinants. However, the similarity stems primarily from the fact that both sets of results are skewed to the right, revealing a high number of considerably efficient observations.

Table 5.23 summarizes results obtained from all the methods used in the analysis. For the sake of clarity, only efficiency scores averaged over the entire period were used. Table 5.23 provides the information for the whole sample as well as for individual groups. Correlation coefficients for the whole sample are very similar to rank correlation coefficients obtained earlier for individual years. Nevertheless, division into size group brings a new insight. Specifically, correlation among methods for the group of the smallest hospitals is significant in all cases. However, correlation between DEA VRS and SFA and DEA VRS and SFA with determinants is insignificant for groups 2 and 3. For group 3, also DEA CRS and DEA VRS correlation is insignificant. The results suggest that with the change of method, smaller hospitals tend to change their rankings less than bigger hospitals. In other words, efficiency results for smaller hospitals are qualitatively more equal across methods than results for bigger hospitals.

Table 5.23: Summary Statistics and Correlations Across Methods, Average Scores

	Obs	Mean	Min	Max	Rank Correlation CRS	VRS	SFA	SFA_det
≤ 10000								
CRS	33	0.710	0.389	1	1			
VRS	33	0.826	0.499	1	0.708***	1		
SFA	33	0.587	0.377	0.950	0.859***	0.496***	1	
SFA_determ	33	0.982	0.948	0.990	0.361**	0.292*	0.321*	1
10000–20000								
CRS	33	0.515	0.108	0.937	1			
VRS	33	0.745	0.429	1	0.581***	1		
SFA	33	0.406	0.090	0.890	0.716***	0.208	1	
SFA_determ	33	0.885	0.657	0.953	0.455***	0.17	0.537***	1
>2000								
CRS	33	0.398	0.205	0.550	1			
VRS	33	0.794	0.579	1	0.017	1		
SFA	33	0.236	0.103	0.389	0.868***	-0.252	1	
SFA_det	33	0.725	0.471	0.882	0.709***	-0.048	0.773***	1
Whole Sample								
CRS	99	0.541	0.108	1	1			
VRS	99	0.788	0.429	1	0.3557***	1		
SFA	99	0.410	0.090	0.950	0.908***	0.151	1	
SFA_determ	99	0.864	0.471	0.990	0.801***	0.126	0.876***	1

Note: *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

5.3 Discussion of Individual Results

In any case, it is believed that Czech hospitals are not on average overly inefficient when potential determinants of inefficiency are identified and taken care of. Averaged individual cross-sectional efficiency scores for SFA with determinants, as well as their respective rankings, are included in Table A.13. Summary statistics of these scores is provided in the bottom panel of Table 5.23. Table 5.24 provides an overview of the number of hospitals classified in each interval. It is visible from the summary in Table 5.24 that even having accounted for determinants, a high level of inefficiency is rather group-specific. It suggests that hospitals classified in these groups are either indeed inefficient, or that when further environmental factors were accounted for, their efficiency would increase.

Table 5.24: Number of Hospitals in Intervals
- SFA with Determinants

interval	Number of observations				
	whole	group 1	group 2	group 3	teaching
<50%	5	0	0	5	5
50%–60%	4	0	0	4	4
60%–70%	4	0	2	2	2
70%–80%	7	0	0	7	0
80%–90%	30	0	15	15	0
90%–100%	49	33	16	0	0
total	99	33	33	33	11

Table 5.25 provides an overview of the least and most efficient hospitals under SFA and under SFA when determinants were included. Individual efficiency scores from SFA with and without determinants together with their rankings are provided in Table A.13.

Table 5.25: Hospitals in Top & Bottom Deciles
SFA vs. SFA with Determinants, Whole Sample

SFA		SFA_det	
top decile	bottom decile	top decile	bottom decile
34	93	68	25
24	64	85	54
40	54	50	35
12	88	34	8
14	35	70	64
85	8	71	91
83	91	80	89
13	25	13	88
70	23	49	92
63	90	40	94

Note: Hospitals are ordered from the most to the least efficient in each decile.

Table 5.25 suggests that the bottom deciles of efficiency distribution of SFA with and without determinants are very similar. In both cases it is dominated by teaching hospitals (there are 11 teaching hospitals in the Czech Republic). The observations which are ranked in the bottom decile under both models include observations 8, 25, 35, 54, 64, 88 and 91 - all teaching hospitals. Under SFA without determinants there were two other hospitals without teaching status, i.e. observations 90 and 93. Hospital 90 approaches patients on very individual basis and hospital 93 is a military hospital. These two are not classified as least efficient anymore when determinants are included. It thus suggests that with the inclusion of determinants, these hospitals improved their relative position in the sample. Bottom decile of SFA with determinants is taken up by teaching hospitals only. Observation 23, which is the last teaching hospital, follows immediately after (as the 11-th least efficient observation).

As far as top decile is concerned, observations belonging there in both cases include 13, 34, 40 and 70. All of them are members of the the group of the smallest hospitals. Two observations from the size group 2 (14 and 24) belong the the top decile in the model without determinants. Surprisingly, however, when determinants were included, only group 1 is represented in the top decile. No observation improved its position from the bottom to the top decile when determinants of inefficiency were considered.

Table 5.26: Hospitals in Top & Bottom Quantiles
SFA vs. SFA with Determinants, Groups

$\leq$ 10000 - Size Group 1			
SFA		SFA_DET	
top	bottom	top	bottom
34	50	68	20
40	2	85	36
12	87	50	22
85	30	34	27
83	26	70	87
10001–20000 - Size Group 2			
SFA		SFA_DET	
top	bottom	top	bottom
24	58	67	6
14	41	14	17
98	17	84	58
78	93	69	90
67	90	43	93
> 20001 - Size Group 3			
SFA		SFA_DET	
top	bottom	top	bottom
60	35	47	91
73	8	31	89
31	91	28	88
28	25	33	92
33	23	72	94

A similar analysis was carried in division into size groups. Five most and least efficient observations in each group under SFA with and without determinants are listed in Table 5.26. In Group 1, only one observation in each quantile stayed the same when determinants were included. It included observation 85 in the top quantile and 87 in the bottom quantile. Observation 50 moved from the bottom to the top 5 observations with the inclusion of determinants.

There was no such enormous improvement in the remaining size groups. Top and bottom 5 observations for groups 2 and 3 were more stable having always two observations unchanged. The bottom quantile of group 2 was an exception having only one different observation under SFA with determinants as opposed to SFA.

Furthermore, shifts in ranks for average efficiency scores between SFA with and without determinants were analyzed for the entire sample. Average shift was by 11 ranks for all 99 observations. Table 5.27 lists 10 most positively and negatively effected hospital and their group affiliations as well as the number of ranks by which the position changed. One notices that a profound positive influence happened in group 1 and hospitals from group 2 deteriorated their rank position most harshly. The results thus suggest that size was not the most decisive factor in explaining high inefficiency since the biggest hospitals did not experience enormous shifts at all.

Table 5.27: Major Improvements & Deteriorations of Ranks, Whole Sample

Improvement			Deterioration		
size	ID	change	size	ID	change
1	50	37	2	24	−45
1	26	33	2	78	− 39
1	30	27	3	60	−34
1	86	25	2	98	−31
1	11	23	2	14	−30
2	75	22	2	39	−23
1	2	19	1	22	−19
2	84	19	2	38	−19
3	74	17	3	73	−18
2	79	17	1	83	−18

Note: Minus denotes deterioration in the position and visa versa.

The most profound changes in ranks for each group are listed in Table 5.28. Once determinants were included, hospitals in group 1 changed the position by 12, in group 2 by 13.5 and in group 3 by 7 ranks on average (either direction). It results that group 2 experienced most turbulent changes when determinants were included. As for teaching hospitals, 5 out of 11 experienced a negative change in ranks, explicitly hospitals 89, 92, 94 which are also listed in Table 5.27 as major deteriorations for the groups. The remaining 6 teaching hospitals improved in ranks, observation 23 by 9, 25 by 7, 35 and 8 by 2 and 54 91 by 1 rank. The biggest improvements in ranks for teaching hospitals were in Southern Bohemia, on the other hand, major deterioration was for teaching hospitals in Prague.

Table 5.28: Major Improvements & Deterioration of Ranks, Groups

≤ 10000 - Group 1			
Improvement		Deterioration	
ID	change	ID	change
50	37	22	−19
26	33	83	−18
30	27	63	−16
86	25	36	−15
11	23	20	−10
10001–20000 - Group 2			
Improvement		Deterioration	
ID	change	ID	change
75	22	24	−45
84	19	78	−39
79	17	98	−31
10	16	14	−30
3	14	39	−23
> 20001 - Group 3			
Improvement		Deterioration	
ID	change	ID	change
74	17	60	−34
47	14	73	−18
23	9	89	−12
55	8	92	−11
77	8	59	−10
		94	−10

Next, intertemporal changes in ranks for SFA with determinants for individual hospitals were analyzed. Efficiency ranks for each hospital were carefully examined and the trend was judged upon. There is, nevertheless, no statistical method behind. Majority of the sample was found to oscillate around the same rank over the whole period. Observations which revealed some trend are listed in Table 5.29. All hospitals which revealed a trend toward increasing relative efficiency were joint-stock companies, i.e. they were transformed into a for-profit public entity sometime during the period examined. On the other hand, except for hospital 19[11], all hospitals which revealed a decreasing trend in relative efficiency over time were not-for-profit public entities. As far as trend in size groups is concerned, increasing trend in relative efficiency has been noticed primarily in groups 1 and 2, decreasing trend has been noticed in all groups about equally.

[11] Observation 19 was a for-profit hospital the whole period. It is however not a joint-stock company, but a limited liability company, which is an exception among Czech hospitals.

Table 5.29: Intertemporal Trend in Relative Efficiency

Increasing ID	size	Decreasing ID	size
2	1	19	1
3	2	22	1
4	2	24	2
5	1	28	3
7	2	29	1
10	2	30	1
13	1	31	3
41	2	32	2
95	2	33	3
96	3	44	2
		46	2
		47	3
		48	2
		51	2
		53	3
		54	3
		55	3

Average efficiency scores from SFA with determinants for individual hospitals were further averaged for each region and ranked. The number of hospitals in each region is given in Table A.4. Table 5.30 shows average efficiency scores and ranks for regions. Karlovarský Region ended up as the most efficient, however, the results should be interpreted with caution since only one hospital from that region was included in the analysis. Furthermore, there were most hospitals from size group 3, i.e. the most inefficient group, in the Vysočina Region. The Capital of Prague has the lowest average efficiency score of all the regions reaching only 0.531 since majority of teaching hospitals, which belong to the least efficient ones in the analysis, are situated in Prague. Indeed, comparison with Table 5.25 reveals that the most bottom 5 observations under SFA with determinants are situated in Prague (observations 91, 89, 88, 92, 94). On the other hand, three from the most efficient hospitals belong to the Ústí Region, i.e. hospitals 68, 70 and 71, and two to the Central Bohemian Region, observations 85 and 80. Comparison of individual and aggregated results however suggests that, except for Prague, efficiency scores for hospitals within regions are rather dispersed.

Table 5.30: Average Efficiency - Regions

	Efficiency	Rank
South Bohemian Region	0.898	5
Hradec Králové Region	0.892	7
Karlovy Vary Region	0.981	1
Liberec Region	0.910	4
South Moravian Region	0.873	10
Olomouc Region	0.875	9
Pardubice Region	0.853	12
Moravian–Silesian Region	0.883	8
Vysočina Region	0.794	13
Plzeň Region	0.892	6
Ústí Region	0.929	2
Central Bohemian Region	0.923	3
Prague	0.531	14
Zlín Region	0.864	11

Chapter 6

SFA in the Thesis and the IES WP

This chapter relates the results from the SFA analysis in the main part of this thesis with the results and methodology in the IES Working Paper 2/2011 which is included in the appendix. The paper draws on the parametric methodology introduced in Section 2.2 and employed in Subsection 5.1.1 and Section 5.2.

The two SFA analyses differ in the utilization of wages in the model. Keeping in mind that wages of doctors and nurses are to a large extent regulated, which is beyond the control of hospitals, the cost function was altered not to account for wages (Jacobs *et al.* 2006, p. 30). Average salaries for districts were used as a determinant of inefficiency instead, in order to, together with a variable for unemployment, account for the labor market effects on efficiency of hospitals.

Based on the comments raised against the master thesis, the estimation with a proper cost function was tested. Average wages for districts, previously used as a determinant, were found to be a good proxy for wages of medical personnel and thus were employed in the cost function.[1] At the same time, the effect of the unemployment variable was excluded from the estimation.

As obvious from Table 5.1 and Table 3 in the IES WP, the estimated variable coefficients in the analysis without determinants, are very similar in terms of signs and values. Moreover, variance of inefficiency in relation to the variance of the composed error, i.e. the parameter γ reaches around 0.94 in both cases. The only difference is that once wages were included into the cost function, the time–invariant alternative of the model proved to be more convenient. As far as

[1]Wages for medical personnel aggregated into districts were unfotunately available only partly from UZIS (2001–2008).

individual efficiency scores without determinants are concerned, they are very similar which is proved by the comparison of Table 5.2 and Table 4 in the IES WP; and Figure 5.1 and Figure 2 in the IES WP. In both cases, mean efficiency reaches around 0.41, with minimum around 0.10, maximum around 0.92 and standard deviation 0.19 for the whole sample. The values are consistent also for disaggregation into groups.

When determinants of inefficiency were taken care of in the second specification, results obtained under both estimations again resemble each other in terms of signs and values of the coefficients, which can be seen in Table 5.15 and Table 5 in the IES WP. The distribution of efficiency scores in Figure 5.3 and Figure 3 in the IES WP also look considerably alike which is further supported by comparison of Table 5.16 and Table 6 in the IES WP. Specifically, mean efficiency reaches around 0.86, minimum 0.5, maximum 0.99 and standard deviation is around 0.14. The same holds when the sample is divided into groups.

It can thus be concluded that in the former estimation (in the main part of this thesis), wages do not capture the full effect of the labor market when included as a determinant. However, when a proper cost function is employed (with wages included in it, rather than as a determinant), they capture the entire effect of the labor market.

Chapter 7

Conclusion

This thesis examined cost efficiency of 99 general hospitals in the Czech Republic in the period 2001–2008. Two frontier methods were employed - non-parametric Data Envelopment Analysis (DEA) and parametric Stochastic Frontier Analysis (SFA). Arguments for a certain level of their complementarity have been found in the literature (Kooreman 1994a; Chirikos & Sear 2000). This thesis thus tested comparability of results obtained from both methods. Having added determinants of inefficiency into the SFA regression, the presence of inefficiency among Czech hospitals was evaluated. At the same time, the thesis aimed at finding the effects of various environmental factors on inefficiency.

Total costs adjusted for inflation were used as the only input variable. Output variables included patient days, doctor/bed and nurse/bed ratios and additionally, technology indices.

At first, the thesis developed a means to account for severity of cases in patient days. Unfortunately, non-operative, operative and intensive care were found to be highly correlated. As a consequence, patient days were adjusted based on the results of the Principal Components Analysis. The types of care which were highly correlated among one another were summed and employed as one variable only.

As expected, all output variables increase costs, however in the analysis without determinants, nursing days probably included some hidden effect in the sign of the coefficient. When determinants of inefficiency were consequently added, even the variable for nursing days behaved as expected.

Additional DEA analysis, which included technology as other output variables, discovered that technology does not shift the frontier in case of Czech hospitals. Rather it has an effect on individual hospitals increasing average efficiency scores for the group as a whole. Efficiency scores of hospitals which were not provided with the data on technology did not change.

Having compared results obtained from different methods, it can be concluded that even though parametric and non-parametric methods work under different assumptions, they are likely to bring to a large extent qualitatively similar results since their purpose is the same - to envelop the data and determine efficiency levels and rankings of individual observations. When estimating the whole sample without determinants, correlation of ranks was significant in all cases but variable returns to scale (VRS) DEA model, since by construction, DEA VRS classifies many observations as fully efficient and thus hampers correlations of rankings. However, when the sample was divided into three groups according to size, it was discovered that rank correlation between DEA VRS and other methods was significant for the group of the smallest hospitals but decreases as group size increases. Therefore, qualitatively similar results across all the methods apply to smaller hospitals only. Qualitatively similar results across all methods, but DEA VRS were obtained for all hospitals.

Rank correlation across methods was further evaluated for the top and bottom decile of the distribution of efficiency scores. In case of Czech hospitals, it has been found that SFA without determinants reveals qualitatively similar results to DEA CRS and DEA VRS by classifying nearly identical hospitals as least and most efficient. The results thus proved the findings of Chirikos & Sear (2000) about the complementarity and comparability of the results of different frontier methods. However, when determinants of inefficiency were included into SFA, the rank correlation of the top and bottom deciles was not significant any more for any of the methods. It suggests that the inclusion of determinants has an asymmetric effect on efficiency scores and thus a direct effect on efficiency rankings.

All determinants included in this thesis were found to have a significant effect on inefficiency. Teaching status increases inefficiency of Czech hospitals since additional costs connected with teaching material, staff, etc. are expected to be incurred. Being a very small hospital decreases inefficiency, while being very big increases it. There are thus expected to be additional costs connected with the management of the complex and large scale care. Not-for-profit status was found to increase inefficiency. These findings support the ongoing privatization process of Czech hospitals, (even though municipalities and regions are very often major shareholders of the newly created joint-stock companies). Size of the population in the municipality where the hospital is situated was found to increase efficiency. The results differ from the initial hypothesis. Nevertheless, it has been acknowledged that population size tends to include a number of effects. As the results show, the effect of more advanced, complex and efficient care in bigger cities overweight the effect of longer waiting times (and costly care afterwards). The share of the elderly in the population tends to increase inefficiency of hospitals. Since this variable was significant at 10 % level at one tail distribution, it was rejected that the share of over-65 population decreases inefficiency. Higher unemployment rate was found to increase efficiency of hospitals consistent with the opportunity cost hypothesis. Specifically, higher unemployment increases opportunity cost of not working, and thus people are more interested in their health, take preventive measures in order to avoid long-term and costly hospital treatments. Average salary in the area decreases efficiency of hospitals. Being a proxy for salaries of medical personnel, costs and thus inefficiency increase as salary rises. The number of hospitals in the region was found to decrease inefficiency, consistent with the hypothesis.

Results, as far as the effect of determinants and its magnitude as well as the distribution of efficiency scores, proved to be very much in accordance when average wages were included into the cost function and the effect of unemployment excluded (in the analysis in the IES WP). It thus suggests that in the former case, the effect of the labor market was dual, however, in the latter estimation, wages in the cost function accounted for the entire labor market effect.

Having accounted for determinants, efficiency scores of all hospitals remarkably increased. It suggests that when these factors were not accounted for, low efficiency scores would have wrongly been considered as inefficiency despite the fact that they are caused by the characteristic features. Furthermore, with the inclusion of determinants, rankings within the group of all hospitals changed considerably suggesting that determinants exerted asymmetric effects on hospitals, depending of the characteristic features of each of the analyzed hospitals. In the whole sample of 99 hospitals, each hospital changed its position by 11 ranks on average when determinants were included (compared to SFA without determinants). On the disaggregated level, the most profound shifts took place in group 2, i.e. in the group of hospitals which take care of between 10,000–20,000 patients a year. Each hospital in group 2 changed its position by 13.5 ranks on average.

Intertemporal trend of increasing and decreasing relative efficiency has been uncovered in a small number of cases. Among these, hospitals with increasing trend of relative efficiency, i.e. higher rank over time, included privatized hospitals exclusively, while the decreasing trend was characteristic for not-for-profit entities. In overall, however, rankings of hospitals within the whole group of 99 units was to a large extent intertemporally stable, i.e. relative position of most hospitals tended to oscillate around the same rank over time.

The results of SFA with determinants reveal that Czech hospitals are not overly inefficient as a whole. Nevertheless, it has been uncovered that the persistence of inefficiency is rather group specific. Put differently, even having accounted for size and teaching status, teaching and very big hospitals in general, i.e. those classified in size group 3, preserve some level of inefficiency. It suggests that these hospitals are either indeed inefficient or when additional determinants of inefficiency were accounted for, their efficiency would increase. In further research, we will concentrate on the identification of these variables.

The thesis has a number of other implications for further research. The panel has been restricted to 8 years of observations in an unbalanced form. Extension to a balanced panel with more observations for each hospital would enable a more extensive intertemporal comparison of the results.

The system of Diagnostic–Related Groups, common abroad a case mix adjustment mechanism in efficiency analyses, is currently being developed in the Czech Republic. Once the system functions fully, variations in output-mix would be accounted for more precisely. The motivation is thus to replicate the results of this thesis once this information is available. At the same time, this thesis should motivate to a more elaborate and responsible data collection in general.

Throughout the thesis, alternative determinants of inefficiency have been proposed. The effect of these should thus be examined in further research. These include accounting directly for wages of medical staff instead of using average salary in the district as a proxy for input prices. The data was however, not available when this analysis was carried out. It has further been suggested that the competition variable take into account distances to other hospitals instead of accounting for the number of hospitals in the region as such. Moreover, the process of transformation of hospitals should be accounted for in further research.

The results of this analysis should not serve as a background for immediate policy responses. It rather points out to special circumstances and provides motivation for further research. At the same time, it is fully acknowledged that economic analysis of Czech hospitals is not telling the whole story. It should be supplemented by surveys of satisfaction with the quality of care, etc. in order for the analysis to provide an overall picture.

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Appendix A

Tables and Figures

Table A.1: Hospitals included in the analysis

ID	Name	ID	Name
1	Nemocnice České Budějovice, a.s.	51	Nemocnice s poliklinikou Nový Jičín, p.o.
2	Nemocnice Český Krumlov, a.s.	52	Bílovecká nemocnice, a.s.
3	Nemocnice Jindřichův Hradec, a.s.	53	Slezská nemocnice v Opavě,p.o.
4	Nemocnice Písek,a.s.	54	FNsP Ostrava
5	Nemocnice Prachatice, a.s.	55	Městská nemocnice Ostrava, p.o.
6	Nemocnice Strakonice, a.s.	56	Nemocnice Havlíčkův Brod, p.o.
7	Nemocnice Tábor, a.s.	57	Nemocnice Jihlava, p.o.
8	Fakultní nemocnice Hradec Králové	58	Nemocnice Pelhřimov, p.o.
9	Oblastní nemocnice Jičín, a.s.	59	Nemocnice Třebíč, p.o.
10	Oblastní nemocnice Náchod, a.s.	60	Nemocnice v N. město na Moravě, p.o.
11	Oblastní nemocnice Rychnov n. Kněžnou, a.s.	61	Domažlická nemocnice, a.s. Domažlice
12	Oblastní Nemocice Náchod, a.s. Opočno	62	Klatovská nemocnice, a.s., Klatovy
13	Městká nemocnice, a.s. Dvůr Králové n. L.	63	Nemocnice Sušice, o.p.s.
14	Oblastní nemocnice Trutnov, a.s.	64	Fakultní nemocnice Plzeň
15	Nemocnice Mariánské Lázně, s.r.o.	65	Stodská nemocnice, a.s., Stod
16	NsP Česká Lípa, a.s.	66	Rokycanská nemocnice, a.s. Rokycany
17	Nemocnice Jablonec n. Nisou, p.o.	67	Krajská zdravotní,a.s. - Nem. Děčín
18	Krajská nemocnice Liberec, a.s.	68	Lužická nemocnice a poliklinika, a.s. Rumburk
19	Nemocnice Frýdlant, s.r.o.	69	Krajská zdravotní, a.s. - Nem. Chomutov, o.z.
20	Masarykova městská nemocnice Jilemnice	70	Nemocnice Kadaň, s.r.o.
21	Panochova nemocnice Turnov, s.r.o.	71	Podřipská NsP Roudnice n. Labem, s.r.o.
22	NsP Semily, p.o.	72	Krajská zdravotní, a.s. - Nemocnice Most, o.z
23	Fakultní nemocnice U sv. Anny, Brno, p.o.	73	Krajská zdravotní, a.s. - Nemocnice Teplice, o.z.
24	Nemocnice Milosrdných Bratří,p.o. Brno	74	Kr. zdrav., a.s. - Masaryk. nem. Ústí n. Lab., o.z.
25	Fakultní nemocnice Brno, Brno	75	Nemocnice Rudolfa a Stefanie Benešov, a.s.
26	Vojenská nemocnice Brno, p.o.	76	NH Hospitals, s.r.o. Nemocnice Hořovice
27	Nemocnice Ivančice, p.o. Ivančice	77	Oblastní nemocnice Kladno, a.s.
28	Nemocnice Břeclav,p.o. Břeclav	78	Nemocnice Slaný, p.o.
29	Městská nemocnice Hustopeče, p.o	79	ON Kolín, a.s.
30	Nemocnice TGM Hodonín, p.o. Hodonín	80	Nemocnice Kutná Hora, s.r.o
31	Nemocnice Kyjov, p.o. Kyjov	81	Mělnická zdravotní, a.s.,NsP Mělník
32	Nemocnice Vyškov, p.o.	82	ON Mladá Boleslav, a.s.
33	Nemocnice Znojmo, p.o.	83	PP Hospitals, s.r.o. Nemocnice Brandýs nad Lab.
34	Jesenická nemocnice, s.r.o., Jeseník	84	Oblastní nemocnice Příbram,a.s.
35	FN Olomouc	85	MEDITERRA - Sedlčany, s. r. o.
36	Vojenská nemocnice, Olomouc, Klášter.Hradisko	86	PRIVAMED Healthia, s.r.o. NsP Rakovnik
37	Středomor. nemocniční,a.s. - Nem. Šternberk	87	Nemocnice Na Františku s poliklinikou
38	Středomor. nemocniční, a.s. - Nem. Prostějov	88	Všeobecná fakultní nemocnice v Praze
39	Středomor. nemocniční, a.s. Přerov	89	Fakultní Thomayerova nemocnice s poliklinikou
40	Nemocnice Hranice, a.s. Hranice	90	Nemocnice na Homolce
41	Chrudimská nemocnice, a.s. Chrudim	91	Fakultní nemocnice Motol
42	Pardubická krajská nemocnice, a.s. Pardubice	92	Fakultní nemocnice Na Bulovce
43	Svitavská nemocnice, a.s. Svitavy	93	Ústřední vojenská nemocnice, Praha 6
44	Nemocnice Krnov, p.o	94	Fakultní nemocnice Královské Vinohrady
45	Nemocnice ve Frýdku-Mistku, p.o	95	Kroměřížská nemocnice, a.s. Kroměříž
46	Nemocnice Třinec, p.o	96	Uherskohradišťská nemocnice,a.s.
47	Nemocnice s poliklinikou, Karviná - Ráj, p.o.	97	Vsetínská nemocnice, a.s., Vsetín
48	Nemocnice s poliklinikou Havířov, p.o.	98	Nemocnice Valašské Meziříčí, a.s.
49	Bohumínská městská nemocnice, a.s. Bohumín	99	Krajská nemocnice T. Bati, a.s. Zlín
50	Karvinská hornická nemocnice, a.s.		

Note: Name valid in the year 2008

Table A.2: Variable Description

INPUT & OUTPUTS

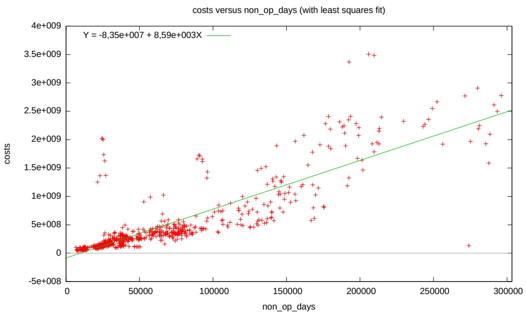
Variable	Description	No. of observations pooled	2004
costs	total costs adjusted for inflation	661	84
sum_3_days	patient days in wards of non-operative operative, intensive care summed	661	84
nursing_days	patient days in nursing wards	370	48
doctor_bed	number of doctors attending one bed per one's work day	660	84
nurse_bed	number of nurses attending one bed per one's work day	660	84
TI_equip	technology index reflecting equipment per 10,000 patients	n.a.	70
TI_proced	technology index reflecting utilization of equipment per patient	n.a.	65

DETERMINANTS

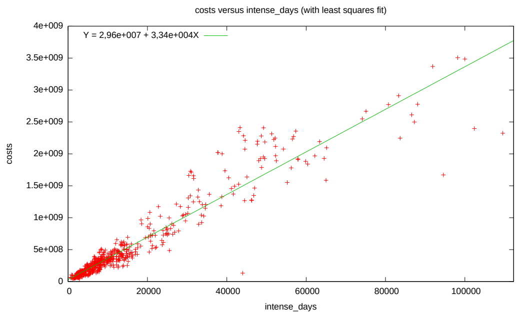
Variable	Description	No. of observations pooled	2004
teaching	dummy indicates teaching status	661	84
size1	less than 10000 treated patients a year	661	84
size3	more than 20001 treated patients a year	661	84
not_profit	not-for-profit form, here owner district, region, municipality	661	84
population	population of municipalities	661	84
over_65	proportion to total municipality population	633	84
unempl	unemployment rate of municipalities with extended powers	661	84
salary	salary of regions	661	84
competition	number of hospitals in the region	661	84

Figure A.1: Input–Output Relations

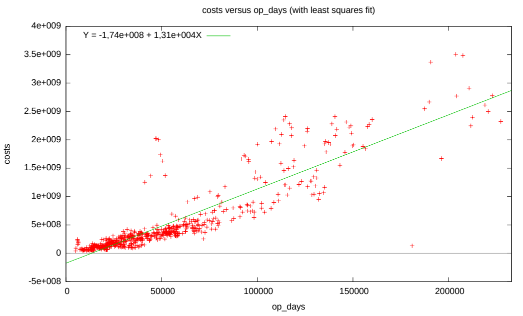
costs vs. non–operative days



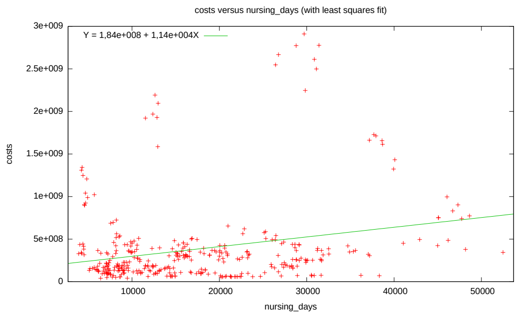
costs vs. intensive days



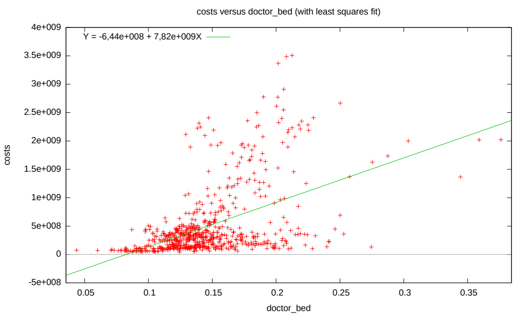
costs vs. operative days



costs vs. nursing days



costs vs. doctors per bed



costs vs. nurses per bed

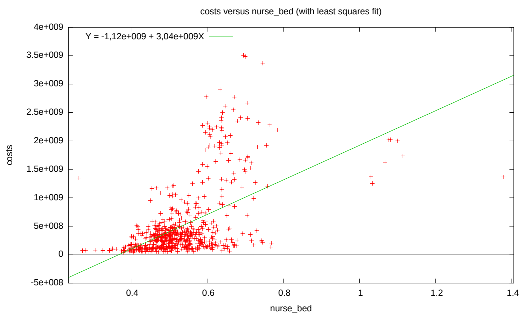


Table A.3: Hospitals Transformed into Joint–Stock Companies in 2006

Size Group 1	Size Group 2	Size Group 3
2	3	1
5	4	16
21	6	18
52	7	82
83	75	96
86	79	99
	81	
	84	
	95	
	97	
	98	

Note: Numbers depict ID numbers of hospitals from Table A.1

Table A.4: Hospitals in Regions

Region	Obs. IDs	No. Obs.
South Bohemian Region	1–7	7
Hradec Králové Region	8–14	7
Karlovy Vary Region	15	1
Liberec Region	16–22	7
South Moravian Region	23–33	11
Olomouc Region	34–40	7
Pardubice Region	41-43	3
Moravian–Silesian Region	44–55	12
Vysočina Region	56–60	5
Plzeň Region	61–66	6
Ústí Region	67-74	8
Central Bohemian Region	75–86	12
Prague	87–94	8
Zlín Region	95–99	5

Table A.5: Size Typology

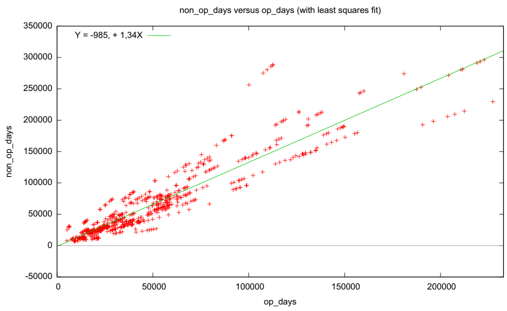
ID	size_group	ID	size_group	ID	size_group
2	1	3	2	1	3
5	1	4	2	8	3
11	1	6	2	16	3
12	1	7	2	18	3
13	1	9	2	23	3
15	1	10	2	25	3
19	1	14	2	28	3
20	1	17	2	31	3
21	1	24	2	33	3
22	1	32	2	35	3
26	1	37	2	42	3
27	1	38	2	45	3
29	1	39	2	47	3
30	1	41	2	53	3
34	1	43	2	54	3
36	1	44	2	55	3
40	1	46	2	56	3
49	1	48	2	57	3
50	1	51	2	59	3
52	1	58	2	60	3
61	1	62	2	64	3
63	1	67	2	72	3
65	1	69	2	73	3
66	1	75	2	74	3
68	1	78	2	77	3
70	1	79	2	82	3
71	1	81	2	88	3
76	1	84	2	89	3
80	1	90	2	91	3
83	1	93	2	92	3
85	1	95	2	94	3
86	1	97	2	96	3
87	1	98	2	99	3
sum	33	sum	33	sum	33

Table A.6: Correlation Matrix - Outputs & Determinants

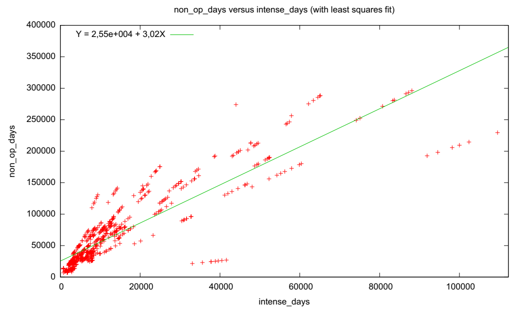
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	
1	0.203	0.3359	0.3641	0.4729	0.3396	0.7922	-0.5427	0.7472	0.3064	0.6564	0.3024	-0.1289	0.4184	0.2074	sum_3_days (1)
	1	-0.0405	-0.1028	0.1233	0.0195	0.238	-0.2517	0.2062	0.0769	0.2143	-0.1376	-0.0783	-0.0328	-0.1626	nursing_days (2)
		1	0.6586	0.5089	0.5134	0.3193	-0.2311	0.1731	0.0662	0.3019	0.2623	-0.2765	0.5261	0.1639	doctor_bed (3)
			1	0.5156	0.546	0.3065	-0.2846	0.2296	0.0638	0.3611	0.2697	-0.2077	0.4157	0.158	nurse_bed(4)
				1	0.658	0.4312	-0.3104	0.3339	0.4035	0.3596	0.1685	-0.1896	0.3278	0.0901	TI_equip (5)
					1	0.318	-0.3073	0.2879	0.1158	0.255	0.2081	-0.1282	0.3279	0.0089	TI_proced (6)
						1	-0.255	0.505	0.2337	0.6352	0.3526	-0.2277	0.4818	0.2562	teaching (7)
							1	-0.5049	-0.3278	-0.2974	-0.0655	0.0425	-0.1338	-0.0665	size1 (8)
								1	0.2937	0.4456	0.0891	-0.0006	0.2961	0.1181	size3 (9)
									1	0.2735	-0.0628	0.1231	-0.0269	0.1843	not_profit (10)
										1	0.3355	-0.0353	0.4478	0.3317	population (11)
											1	-0.476	0.4357	0.0713	over_65 (12)
												1	-0.4465	0.0861	unempl (13)
													1	0.4375	salary (14)
														1	competition (15)

Figure A.2: Correlation Plots - Types of Patient Days

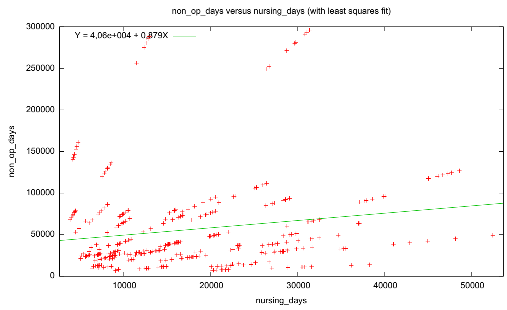
non–operative vs. operative



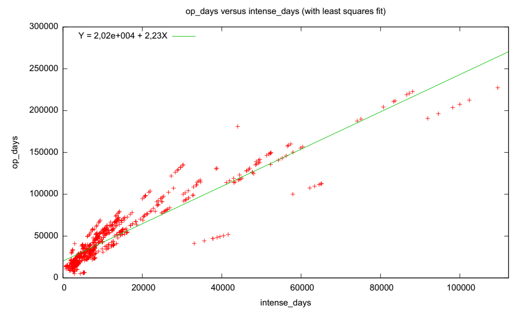
non–operative vs. intensive



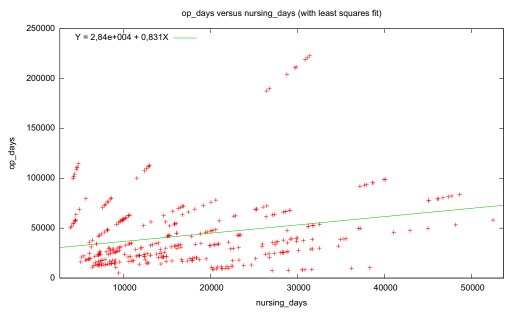
non–operative vs. nursing



operative vs. intensive



operative vs. nursing



intensive vs. nursing

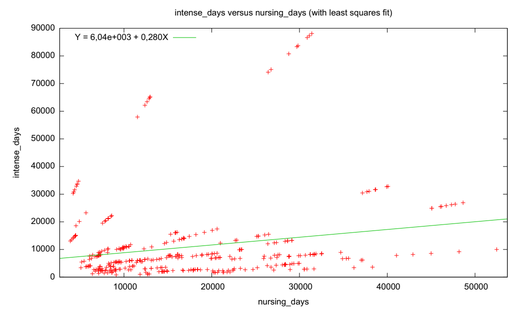
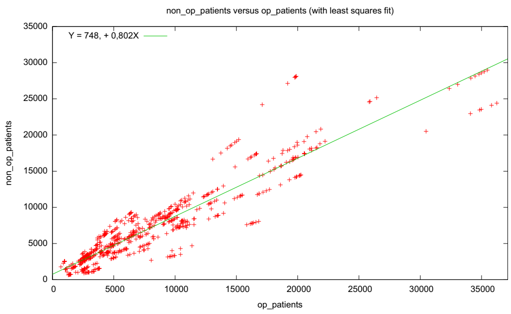
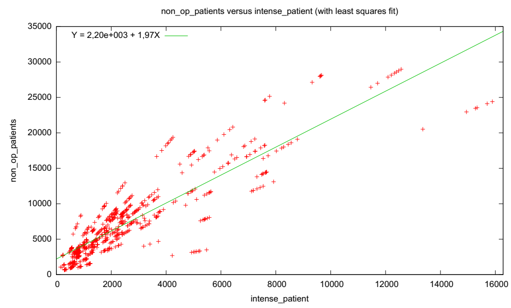


Figure A.3: Correlation Plots - Types of Patients

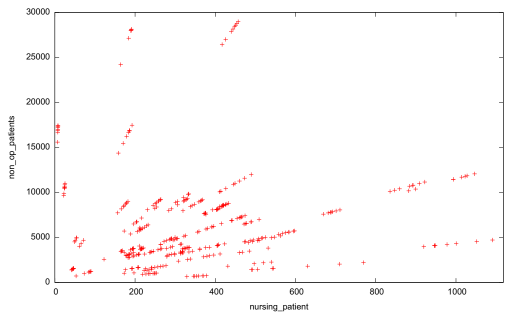
non–operative vs. operative



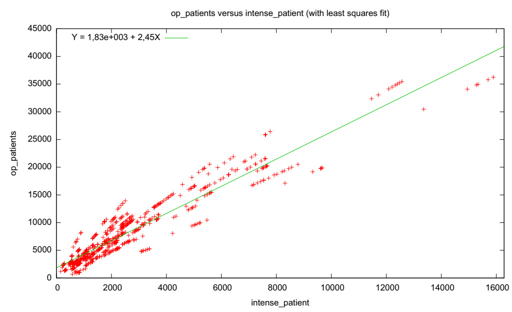
non–operative vs. intensive



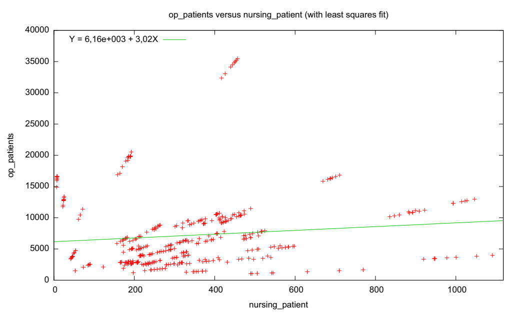
non–operative vs. nursing



operative vs. intensive



operative vs. nursing



intensive vs. nursing

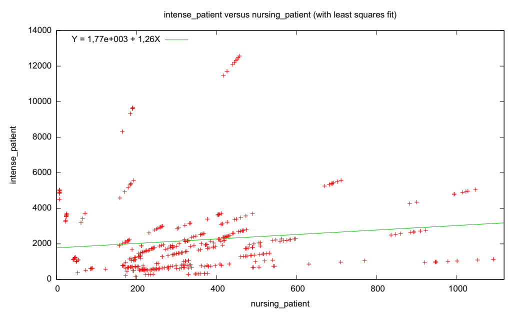


Table A.7: Efficiency Scores & Ranks - SFA without Determinants

size	ID	2001 efficiency	2001 rank	2002 efficiency	2002 rank	2003 efficiency	2003 rank	2004 efficiency	2004 rank	2005 efficiency	2005 rank	2006 efficiency	2006 rank	2007 efficiency	2007 rank	2008 efficiency	2008 rank
3	1	0.228	66	0.221	72	.	.	.	.	.	.	0.197	78	0.191	66	0.185	75
1	2	0.444	32	0.437	32	0.430	30	0.423	32	0.417	32	0.410	36	0.403	30	0.396	35
2	3	0.329	52	0.322	54	0.316	53	0.309	56	0.302	55	0.295	61	0.288	51	0.282	59
2	4	0.492	25	0.486	24	0.479	24	0.472	25	0.466	25	0.459	27	0.452	23	0.445	26
1	5	0.619	11	0.613	11	0.607	10	0.602	12	0.596	13	0.590	14	0.584	13	0.578	13
2	6	0.402	39	0.395	42	0.388	40	0.381	43	0.374	41	0.368	46	0.361	39	0.354	45
2	7	0.350	47	0.344	49	0.337	48	0.330	51	0.323	49	0.316	55	0.309	46	0.302	53
3	8	0.131	74	0.126	79	0.121	76	0.116	81	0.111	81	0.107	87	0.102	75	0.098	85
2	9	0.483	27	0.476	27	0.470	26	0.463	28	0.456	28	0.449	31	0.443	26	0.436	30
2	10	0.380	43	0.373	45	0.366	43	0.359	46	0.352	44	0.345	50	0.338	41	.	.
1	11	.	.	.	.	.	.	0.471	26	0.465	26	0.458	28	0.451	24	0.444	27
1	12	.	.	0.893	2	0.891	2	0.889	3	0.887	4	0.885	4	0.883	4	.	.
1	13	0.775	4	0.771	4	0.767	4	0.763	5	0.759	6	0.755	7	0.751	6	0.747	6
2	14	0.886	2	0.884	3	0.882	3	0.879	4	0.877	5	0.875	5	0.873	5	0.871	4
1	15	0.511	23	.	.	.	.	.	.	0.485	22	0.478	24	0.471	20	0.465	23
3	16	0.271	60	0.265	66	0.258	65	0.252	68	0.245	67	0.239	73	0.232	61	0.226	70
2	17	0.293	57	0.286	63	0.280	62	0.273	65	0.266	64	0.260	70	0.253	58	0.247	67
3	18	0.228	65	0.222	71	0.216	69	0.210	72	0.203	71	0.197	77	0.191	65	0.185	74
1	19	.	.	0.561	16	0.555	14	0.549	16	0.543	17	0.536	18	0.530	16	0.524	17
1	20	0.590	14	0.584	14	0.578	13	0.572	15	0.566	15	0.560	16	0.554	15	0.547	15
1	21	0.520	20	0.514	21	0.507	19	0.501	21	0.494	21	0.487	22	0.481	19	0.474	21
1	22	0.673	8	.	.	.	.	0.658	9	0.653	10	0.647	11	0.642	10	0.636	10
3	23	.	.	0.117	80	0.112	77	0.108	82	0.103	82	0.099	88	0.095	76	0.090	86
2	24	0.897	1	0.895	1	0.893	1	0.891	2	0.889	3	0.887	3	0.885	3	0.883	3
3	25	0.121	75	0.116	81	0.112	78	0.107	83	0.103	83	0.098	89	0.094	77	0.090	87
1	26	.	.	.	.	.	.	0.390	38	0.384	37	0.377	41	0.370	36	0.363	41
1	27	0.488	26	0.482	25	0.475	25	0.468	27	0.462	27	0.455	29	0.448	25	0.441	28
3	28	0.363	46	0.356	48	0.349	47	0.342	50	0.335	48	0.328	54	0.322	45	0.315	52
1	29	0.676	7	0.671	7	0.666	6	0.661	8	0.656	9	0.651	10	0.645	9	0.640	9
1	30	0.409	38	0.402	40	0.395	38	0.388	41	0.381	39	0.374	44	0.367	38	0.360	43
3	31	0.364	45	0.357	47	0.350	46	0.343	49	0.336	47	0.330	53	0.323	44	0.316	51
2	32	.	.	.	.	0.322	52	0.316	55	0.309	54	0.302	60	0.295	50	0.288	58
3	33	.	.	.	.	0.356	45	0.349	48	0.342	46	0.335	52	0.328	43	0.321	50

Efficiency Scores & Ranks - SFA without Determinants cont'd

size	ID	2001 efficiency	2001 rank	2002 efficiency	2002 rank	2003 efficiency	2003 rank	2004 efficiency	2004 rank	2005 efficiency	2005 rank	2006 efficiency	2006 rank	2007 efficiency	2007 rank	2008 efficiency	2008 rank
1	34	.	.	.	.	.	.	0.952	1	0.951	1	0.950	1	0.949	1	0.948	1
3	35	0.135	72	0.130	78	0.125	75	0.120	79	0.115	79	0.110	85	0.106	73	0.101	83
1	36	.	.	0.620	9	0.614	8	0.609	11	0.603	12	0.597	13	0.591	12	0.585	12
2	37	0.430	33	0.423	33	0.416	31	0.409	33	0.402	33	0.396	37	0.389	31	0.382	36
2	38	.	.	0.421	34	0.415	32	0.408	34	0.401	34	0.394	38	0.387	32	0.380	37
2	39	0.451	30	.	.	.	.	.	.	0.424	30	0.417	34	0.410	28	0.403	33
1	40	.	.	.	.	.	.	.	.	0.891	2	0.889	2	0.887	2	0.885	2
2	41	.	.	0.317	57	0.310	56	0.303	59	0.296	58	0.289	64	0.283	53	0.276	62
3	42	0.267	62	0.260	68	0.254	66	0.247	69	0.241	68	0.234	74	0.228	62	0.221	71
2	43	0.481	28	0.475	28	0.468	27	0.461	29	.	.	.	.	.	.	.	.
2	44	.	.	0.405	36	0.398	34	0.391	36	0.384	36	0.377	40	0.370	34	0.364	39
3	45	0.284	58	0.278	64	0.271	63	0.264	66	0.258	65	0.251	71	0.245	59	0.238	68
2	46	0.372	44	0.365	46	0.358	44	0.351	47	0.344	45	0.337	51	0.330	42	0.323	49
3	47	.	.	0.318	56	0.312	55	0.305	58	0.298	57	0.291	63	0.284	52	0.278	61
2	48	0.409	37	0.402	39	0.395	37	0.388	40	0.381	38	0.374	43	0.368	37	0.361	42
1	49	0.532	19	0.526	20	0.520	18	0.513	20	.	.	.	.	.	.	.	.
1	50	.	.	0.445	30	0.438	28	0.431	30	0.425	29	0.418	33	0.411	27	0.404	32
2	51	0.450	31	0.443	31	0.436	29	0.429	31	0.422	31	0.415	35	0.409	29	0.402	34
1	52	0.565	16	0.559	17	0.553	15	0.547	17	0.540	18	0.534	19	0.528	17	0.521	18
3	53	0.337	51	0.330	53	0.323	51	0.316	54	0.310	53	0.303	59	0.296	49	0.289	57
3	54	0.152	70	0.147	77	0.142	74	0.136	77	0.131	77	0.126	83	0.121	71	0.117	81
3	55	0.295	56	0.288	62	0.281	61	0.275	64	0.268	63	0.261	69	0.255	57	0.248	66
3	56	.	.	0.305	59	0.299	58	0.292	61	0.285	60	0.278	66	.	.	.	.
3	57	0.264	63	0.258	69	0.251	67	0.245	70	0.238	69	0.232	75	0.225	63	0.219	72
2	58	0.323	53	0.316	58	0.309	57	0.303	60	0.296	59	0.289	65	0.282	54	0.275	63
3	59	0.341	50	0.334	52	0.327	50	0.321	53	0.314	52	0.307	58	0.300	48	0.293	56
3	60	0.411	35	0.404	37	0.398	35	0.391	37	.	.	.	.	0.370	35	0.363	40
1	61	0.539	18	0.533	19	0.527	17	0.520	19	0.514	20	0.507	21	0.501	18	0.494	20
2	62	.	.	.	.	0.487	22	0.480	23	0.474	23	0.467	25	0.460	21	0.453	24
1	63	0.735	6	0.731	6	0.727	5	0.722	7	0.718	8	0.713	9	0.709	8	0.704	8
3	64	0.153	69	0.147	76	0.142	73	0.137	76	0.132	76	0.127	82	0.122	70	0.117	80
1	65	0.632	9	0.627	8	0.621	7	0.616	10	0.610	11	0.604	12	0.598	11	0.593	11
1	66	0.496	24	0.489	23	0.483	23	0.476	24	0.469	24	0.463	26	0.456	22	0.449	25

Efficiency Scores & Ranks - SFA without Determinants cont'd

size	ID	2001 efficiency	2001 rank	2002 efficiency	2002 rank	2003 efficiency	2003 rank	2004 efficiency	2004 rank	2005 efficiency	2005 rank	2006 efficiency	2006 rank	2007 efficiency	2007 rank	2008 efficiency	2008 rank
2	67	0.517	21	.	.	0.504	20	.	.	.	.	.	.	.	.	0.471	22
1	68	0.593	13	0.587	13	0.581	12	0.575	14	.	.	.	.	.	.	.	.
2	69	0.457	29	0.451	29	.	.	.	.	.	.	0.423	32	.	.	0.409	31
1	70	0.744	5	0.740	5	.	.	0.731	6	0.727	7	0.723	8	0.718	7	0.714	7
1	71	0.596	12	0.590	12	0.584	11	0.578	13	0.572	14	0.566	15	0.560	14	0.554	14
3	72	.	.	0.321	55	0.314	54	0.307	57	0.300	56	0.294	62	.	.	0.280	60
3	73	.	.	0.400	41	0.393	39	0.386	42	0.379	40	0.372	45	.	.	0.358	44
3	74	0.184	68	0.179	75	0.173	72	0.167	75	0.162	74	0.156	81	.	.	0.145	78
2	75	0.346	48	0.339	50	0.332	49	0.326	52	0.319	50	0.312	56	0.305	47	0.298	54
1	76	0.512	22	0.506	22	0.499	21	0.493	22	.	.	0.480	23	.	.	.	.
3	77	0.271	61	0.265	67	.	.	.	.	.	.	.	.	.	.	.	.
2	78	0.557	17	0.551	18	0.545	16	0.539	18	0.532	19	0.526	20	.	.	0.513	19
2	79	0.346	49	0.339	51	.	.	.	.	0.318	51	0.311	57	.	.	0.298	55
1	80	0.574	15	0.568	15	.	.	.	.	0.550	16	0.543	17	.	.	0.531	16
2	81	0.380	42	0.373	44	0.366	42	0.359	45	.	.	0.345	49	.	.	0.332	48
3	82	0.305	55	0.298	61	0.291	60	0.284	63	0.277	62	0.271	68	0.264	56	0.257	65
1	83	.	.	.	.	.	.	.	.	.	.	0.779	6	.	.	0.771	5
2	84	0.389	41	.	.	.	.	.	.	0.361	43	0.354	48	.	.	0.340	47
1	85	0.814	3	.	.	.	.	.	.	.	.	.	.	.	.	.	.
1	86	.	.	0.481	26	.	.	.	.	.	.	0.454	30	.	.	0.440	29
1	87	0.413	34	0.406	35	0.399	33	0.392	35	0.385	35	0.378	39	0.372	33	0.365	38
3	88	0.145	71	.	.	.	.	0.130	78	0.125	78	0.120	84	0.115	72	0.111	82
3	89	0.261	64	0.254	70	0.247	68	0.241	71	0.234	70	0.228	76	0.222	64	0.216	73
2	90	0.104	76	0.100	82	0.096	79	0.092	84	0.088	84	0.084	90	0.080	78	0.076	88
3	91	0.133	73	.	.	.	.	0.119	80	0.114	80	0.109	86	0.105	74	0.100	84
3	92	0.218	67	0.211	73	0.205	70	0.199	73	0.193	72	0.187	79	0.181	67	0.176	76
2	93	.	.	.	.	.	.	.	.	0.151	75	.	.	0.140	69	0.135	79
3	94	.	.	0.180	74	0.174	71	0.169	74	0.163	73	0.157	80	0.152	68	0.147	77
2	95	0.395	40	0.388	43	0.381	41	0.374	44	0.367	42	0.360	47	0.353	40	0.346	46
3	96	0.311	54	0.304	60	0.298	59	0.291	62	0.284	61	0.277	67	0.271	55	0.264	64
2	97	0.411	36	0.404	38	0.397	36	0.390	39	.	.	0.376	42	.	.	.	.
2	98	0.622	10	0.617	10	0.611	9	.	.	.	.	.	.	.	.	.	.
3	99	0.278	59	0.271	65	0.264	64	0.258	67	0.251	66	0.245	72	0.238	60	0.232	69

Table A.8: Efficiency Scores & Ranks - DEA CRS

size	ID	2001 efficiency	2001 rank	2002 efficiency	2002 rank	2003 efficiency	2003 rank	2004 efficiency	2004 rank	2005 efficiency	2005 rank	2006 efficiency	2006 rank	2007 efficiency	2007 rank	2008 efficiency	2008 rank
3	1	0.378	64	0.376	71	.	.	.	.	.	.	0.096	77	0.480	51	0.431	68
1	2	0.581	28	0.558	46	0.635	25	0.635	21	0.590	32	0.525	14	0.737	15	0.663	21
2	3	0.479	46	0.481	55	0.463	60	0.416	66	0.401	70	0.216	56	0.502	44	0.491	52
2	4	0.518	41	0.584	38	0.652	23	0.635	21	0.633	20	0.260	45	0.548	36	0.554	42
1	5	0.659	17	0.723	19	0.661	22	0.615	26	0.604	27	0.398	28	0.594	26	0.600	32
2	6	0.631	19	0.694	23	0.497	53	0.485	57	0.527	48	0.221	53	0.496	46	0.486	55
2	7	0.554	32	0.507	53	0.538	41	0.516	54	0.592	30	0.232	50	0.629	19	0.637	26
3	8	0.259	75	0.255	80	0.240	78	0.231	82	0.227	81	0.048	89	0.262	73	0.262	83
2	9	0.440	52	0.452	61	0.578	37	0.578	36	0.700	14	0.253	47	0.614	23	0.594	34
2	10	0.537	36	0.559	45	0.668	20	0.631	23	0.607	26	0.373	32	0.660	17	.	.
1	11	.	.	.	.	.	.	0.602	29	0.598	29	0.415	25	0.590	28	0.611	31
1	12	.	.	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	.	.
1	13	0.615	21	0.911	10	0.989	6	0.967	8	1.000	1	0.847	7	1.000	1	1.000	1
2	14	0.952	6	0.967	7	1.000	1	1.000	1	0.982	8	0.593	11	1.000	1	1.000	1
1	15	0.479	46	.	.	.	.	.	.	0.587	33	0.515	16	0.565	33	0.892	11
3	16	0.370	67	0.379	70	0.419	63	0.622	24	0.494	52	0.294	38	0.371	65	0.388	73
2	17	0.314	72	0.361	73	0.386	70	0.393	71	0.458	59	0.284	41	0.448	58	0.451	65
3	18	0.421	57	0.454	59	0.505	51	0.480	60	0.423	65	0.182	65	0.791	10	0.396	72
1	19	.	.	0.961	8	0.764	11	0.771	12	0.641	19	0.573	12	0.668	16	0.794	16
1	20	0.573	30	0.671	25	0.789	9	0.567	37	0.581	34	0.472	18	0.569	31	0.672	20
1	21	0.657	18	0.706	22	0.606	32	0.593	32	0.568	39	0.442	23	0.481	50	0.691	19
1	22	0.611	22	.	.	.	.	0.612	27	0.787	10	0.644	10	0.800	9	0.979	7
3	23	.	.	0.262	79	0.250	76	0.203	83	0.207	83	0.082	78	0.212	77	0.221	87
2	24	1.000	1	1.000	1	0.978	7	1.000	1	1.000	1	0.519	15	0.984	8	0.957	9
3	25	0.332	69	0.342	76	0.314	73	0.318	78	0.279	77	0.076	80	0.317	69	0.324	79
1	26	.	.	.	.	.	.	0.410	67	0.387	72	0.253	47	0.422	62	0.472	61
1	27	0.679	13	0.669	27	0.475	57	0.520	53	0.626	21	0.403	27	0.582	29	0.723	18
3	28	0.396	63	0.468	57	0.509	50	0.538	48	0.671	17	0.226	52	0.647	18	0.662	22
1	29	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
1	30	0.508	44	0.516	50	0.529	46	0.477	61	0.417	66	0.310	37	0.436	59	0.484	58
3	31	0.554	32	0.512	52	0.583	35	0.582	34	0.599	28	0.220	54	0.611	24	0.653	24
2	32	.	.	.	.	0.664	21	0.655	20	0.546	46	0.276	43	0.557	35	0.563	40
3	33	.	.	.	.	0.607	31	0.590	33	0.581	34	0.140	72	0.566	32	0.626	29

Efficiency Scores & Ranks - DEA CRS cont'd

size	ID	2001		2002		2003		2004		2005		2006		2007		2008	
		efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank
1	34	.	.	.	.	.	.	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
3	35	0.278	74	0.240	81	0.248	77	0.235	81	0.224	82	0.051	88	0.225	75	0.258	84
1	36	.	.	0.788	12	0.700	15	0.657	19	0.625	24	0.353	35	0.610	25	0.772	17
2	37	0.530	37	0.573	39	0.524	47	0.579	35	0.568	39	0.447	21	0.429	61	0.591	36
2	38	.	.	0.567	42	0.520	48	0.540	46	0.571	37	0.208	57	0.622	20	0.654	23
2	39	0.528	38	.	.	.	.	.	.	0.400	71	0.287	40	0.515	40	0.537	48
1	40	.	.	.	.	.	.	.	.	0.784	11	1.000	1	0.767	12	0.879	12
2	41	.	.	0.383	69	0.386	70	0.384	73	0.526	49	0.374	31	0.571	30	0.541	47
3	42	0.414	60	0.412	65	0.412	65	0.409	68	0.425	63	0.121	75	0.422	62	0.433	67
2	43	0.617	20	0.621	31	0.574	39	0.526	52	.	.	.	.	.	.	.	.
2	44	.	.	0.742	15	0.701	14	0.744	15	0.686	16	0.290	39	0.451	57	0.470	62
3	45	0.416	59	0.405	67	0.413	64	0.406	69	0.424	64	0.172	68	0.452	56	0.435	66
2	46	0.681	12	0.671	25	0.625	27	0.555	41	0.556	44	0.195	61	0.540	39	0.491	52
3	47	.	.	0.658	28	0.651	24	0.699	18	0.626	21	0.177	67	0.504	43	0.485	57
2	48	0.484	45	0.572	40	0.537	42	0.545	44	0.579	36	0.198	60	0.490	47	0.486	55
1	49	0.677	15	0.708	20	0.748	12	0.741	16	.	.	.	.	.	.	.	.
1	50	.	.	1.000	1	0.611	30	0.460	62	0.413	67	0.407	26	0.349	67	0.404	71
2	51	0.516	42	0.529	48	0.535	43	0.550	42	0.569	38	0.240	49	0.559	34	0.543	45
1	52	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
3	53	0.469	48	0.439	64	0.389	69	0.432	64	0.451	62	0.152	70	0.477	52	0.492	51
3	54	0.292	73	0.286	78	0.297	74	0.279	79	0.273	79	0.056	86	0.269	72	0.274	82
3	55	0.608	23	0.632	29	0.629	26	0.602	29	0.568	39	0.123	74	0.490	47	0.507	49
3	56	.	.	0.481	55	0.490	55	0.532	50	0.551	45	0.195	61	.	.	.	.
3	57	0.546	35	0.560	44	0.501	52	0.545	44	0.480	57	0.178	66	0.457	55	0.414	69
2	58	0.428	55	0.440	62	0.445	62	0.431	65	0.407	68	0.255	46	0.433	60	0.409	70
3	59	0.421	57	0.916	9	0.625	27	0.508	55	0.609	25	0.217	55	0.509	41	0.504	50
3	60	0.520	40	0.592	36	0.592	34	0.559	39	.	.	.	.	0.473	53	0.480	59
1	61	0.692	11	0.726	18	0.684	18	0.747	14	0.693	15	0.472	18	0.617	22	0.621	30
2	62	.	.	.	.	0.471	58	0.534	49	0.520	51	0.351	36	0.541	38	0.546	43
1	63	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	0.922	6	1.000	1	0.904	10
3	64	0.323	71	0.304	77	0.280	75	0.277	80	0.279	77	0.056	86	0.312	70	0.336	78
1	65	0.752	8	0.728	17	0.847	8	0.920	9	0.824	9	0.723	8	0.746	13	0.805	15
1	66	0.525	39	0.610	33	0.579	36	0.608	28	0.564	42	0.495	17	0.740	14	0.963	8

Efficiency Scores & Ranks - DEA CRS cont'd

size	ID	2001 efficiency	2001 rank	2002 efficiency	2002 rank	2003 efficiency	2003 rank	2004 efficiency	2004 rank	2005 efficiency	2005 rank	2006 efficiency	2006 rank	2007 efficiency	2007 rank	2008 efficiency	2008 rank
2	67	0.708	10	.	.	0.675	19	.	.	.	.	.	.	.	.	0.600	32
1	68	0.750	9	0.676	24	0.690	17	0.713	17	.	.	.	.	.	.	.	.
2	69	0.580	29	0.617	32	.	.	.	.	.	.	0.279	42	.	.	0.638	25
1	70	0.594	26	0.734	16	.	.	0.789	10	0.782	12	0.547	13	0.777	11	0.831	13
1	71	0.678	14	0.898	11	0.787	10	0.761	13	0.666	18	0.371	33	0.620	21	0.590	37
3	72	.	.	0.516	50	0.514	49	0.547	43	0.524	50	0.145	71	.	.	0.543	45
3	73	.	.	0.568	41	0.561	40	0.556	40	0.535	47	0.205	58	.	.	0.593	35
3	74	0.414	60	0.453	60	0.403	68	0.347	74	0.313	74	0.076	80	.	.	0.341	77
2	75	0.566	31	0.565	43	0.531	45	0.539	47	0.457	60	0.265	44	0.484	49	0.461	64
1	76	0.588	27	0.707	21	0.578	37	0.531	51	.	.	0.392	29	.	.	.	.
3	77	0.331	70	0.351	74	.	.	.	.	.	.	.	.	.	.	.	.
2	78	0.552	34	0.771	14	0.734	13	0.777	11	0.750	13	0.371	33	.	.	0.823	14
2	79	0.431	54	0.400	68	.	.	.	.	0.481	55	0.155	69	.	.	0.463	63
1	80	0.764	7	0.788	12	.	.	.	.	0.626	21	0.469	20	.	.	0.633	27
2	81	0.462	50	0.534	47	0.601	33	0.602	29	.	.	0.445	22	.	.	0.589	38
3	82	0.373	65	0.371	72	0.411	66	0.405	70	0.452	61	0.140	72	0.499	45	0.324	79
1	83	.	.	.	.	.	.	.	.	.	.	0.667	9	.	.	1.000	1
2	84	0.424	56	.	.	.	.	.	.	0.486	53	0.192	63	.	.	0.487	54
1	85	1.000	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.
1	86	.	.	0.503	54	.	.	.	.	.	.	0.436	24	.	.	0.629	28
1	87	0.467	49	0.600	35	0.532	44	0.564	38	0.564	42	0.385	30	0.509	41	0.574	39
3	88	0.373	65	.	.	.	.	0.326	76	0.310	75	0.070	84	0.354	66	0.357	76
3	89	0.601	25	0.630	30	0.488	56	0.481	59	0.479	58	0.074	83	0.343	68	0.366	75
2	90	0.114	76	0.132	82	0.110	79	0.100	84	0.087	84	0.069	85	0.096	78	0.154	88
3	91	0.365	68	.	.	.	.	0.325	77	0.303	76	0.042	90	0.223	76	0.232	86
3	92	0.407	62	0.407	66	0.404	67	0.389	72	0.406	69	0.079	79	0.390	64	0.387	74
2	93	.	.	.	.	.	.	.	.	0.231	80	.	.	0.234	74	0.246	85
3	94	.	.	0.346	75	0.332	72	0.336	75	0.333	73	0.075	82	0.300	71	0.321	81
2	95	0.453	51	0.456	58	0.497	53	0.496	56	0.481	55	0.192	63	0.542	37	0.544	44
3	96	0.603	24	0.589	37	0.623	29	0.618	25	0.591	31	0.231	51	0.591	27	0.556	41
2	97	0.436	53	0.440	62	0.458	61	0.454	63	.	.	0.202	59	.	.	.	.
2	98	0.669	16	0.603	34	0.694	16	.	.	.	.	.	.	.	.	.	.
3	99	0.511	43	0.520	49	0.467	59	0.483	58	0.486	53	0.105	76	0.470	54	0.477	60

Table A.9: Efficiency Scores & Ranks - DEA VRS

size	ID	2001 efficiency	2001 rank	2002 efficiency	2002 rank	2003 efficiency	2003 rank	2004 efficiency	2004 rank	2005 efficiency	2005 rank	2006 efficiency	2006 rank	2007 efficiency	2007 rank	2008 efficiency	2008 rank
3	1	1.000	1	1.000	1	.	.	.	.	.	.	0.125	83	1.000	1	1.000	1
1	2	0.887	34	0.930	30	1.000	1	0.856	51	0.822	52	0.986	19	1.000	1	1.000	1
2	3	0.784	44	0.577	69	0.599	71	0.515	83	0.514	81	0.312	55	0.637	56	0.728	66
2	4	0.619	73	0.600	68	0.810	47	0.870	45	0.777	57	0.269	62	0.765	45	0.691	73
1	5	0.728	54	0.729	52	0.673	63	0.617	77	0.617	75	0.398	48	0.675	53	0.600	83
2	6	0.845	37	0.710	54	0.560	75	0.560	81	0.635	68	0.235	66	0.550	72	0.609	82
2	7	0.858	36	0.570	70	0.849	39	0.784	60	0.907	39	0.371	50	1.000	1	1.000	1
3	8	0.631	70	0.661	61	0.730	59	0.608	78	0.634	69	0.061	90	0.834	35	0.715	69
2	9	0.463	76	0.459	79	0.647	67	1.000	1	0.914	36	0.277	61	0.984	26	0.808	55
2	10	1.000	1	0.897	33	1.000	1	0.870	45	0.951	33	1.000	1	0.906	28	.	.
1	11	.	.	.	.	.	.	1.000	1	1.000	1	1.000	1	0.773	44	0.878	47
1	12	.	.	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	.	.
1	13	0.626	71	0.971	25	1.000	1	1.000	1	1.000	1	0.884	22	1.000	1	1.000	1
2	14	1.000	1	1.000	1	1.000	1	1.000	1	0.988	29	0.683	28	1.000	1	1.000	1
1	15	0.638	69	.	.	.	.	.	.	0.599	76	0.551	37	0.601	66	0.964	42
3	16	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	0.823	36	1.000	1
2	17	0.776	46	1.000	1	1.000	1	1.000	1	0.837	49	0.602	32	0.580	68	0.730	65
3	18	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
1	19	.	.	0.962	26	0.827	44	1.000	1	0.719	63	0.752	23	0.774	43	0.818	53
1	20	0.720	56	0.672	60	0.874	35	0.883	44	0.587	77	0.479	42	0.610	63	0.711	70
1	21	0.803	41	1.000	1	1.000	1	0.917	37	0.760	60	0.752	23	0.553	71	1.000	1
1	22	0.780	45	.	.	.	.	0.856	51	0.947	34	0.650	30	1.000	1	0.980	38
3	23	.	.	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	0.636	80
2	24	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	0.528	40	1.000	1	1.000	1
3	25	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
1	26	.	.	.	.	.	.	0.504	84	0.387	84	0.320	53	0.500	76	0.783	58
1	27	0.803	41	0.710	54	0.476	77	0.714	71	0.742	61	0.407	46	0.666	54	0.966	41
3	28	0.642	68	0.553	72	0.717	61	0.894	39	1.000	1	0.256	64	0.816	37	0.975	39
1	29	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
1	30	1.000	1	0.810	42	0.806	49	0.736	69	0.501	82	0.548	38	0.517	74	0.511	88
3	31	0.835	40	0.568	71	0.837	40	0.887	41	0.899	42	0.268	63	0.867	33	1.000	1
2	32	.	.	.	.	1.000	1	0.950	31	0.903	40	0.564	36	0.705	51	1.000	1
3	33	.	.	.	.	0.954	26	0.974	30	1.000	1	0.157	78	0.765	45	1.000	1

Efficiency Scores & Ranks - DEA VRS cont'd

size	ID	2001 efficiency	2001 rank	2002 efficiency	2002 rank	2003 efficiency	2003 rank	2004 efficiency	2004 rank	2005 efficiency	2005 rank	2006 efficiency	2006 rank	2007 efficiency	2007 rank	2008 efficiency	2008 rank
1	34	.	.	.	.	.	.	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
3	35	0.844	38	0.861	37	0.858	37	0.790	59	0.824	50	0.158	77	0.722	48	0.723	67
1	36	.	.	0.788	44	0.731	58	0.665	74	0.627	71	0.363	51	0.624	59	0.772	60
2	37	1.000	1	1.000	1	0.670	64	1.000	1	1.000	1	1.000	1	0.900	30	0.821	51
2	38	.	.	0.641	65	0.730	59	0.863	49	0.897	43	0.213	67	0.806	38	0.990	36
2	39	0.918	30	.	.	.	.	.	.	0.471	83	0.296	56	0.593	67	0.598	84
1	40	.	.	.	.	.	.	.	.	1.000	1	1.000	1	1.000	1	1.000	1
2	41	.	.	1.000	1	0.810	47	0.630	76	0.812	54	1.000	1	1.000	1	1.000	1
3	42	0.725	55	0.689	58	0.902	30	0.868	48	0.900	41	0.145	80	0.857	34	0.970	40
2	43	0.750	52	0.638	66	0.611	69	0.806	58	.	.	.	.	.	.	.	.
2	44	.	.	1.000	1	1.000	1	1.000	1	1.000	1	0.673	29	1.000	1	0.821	51
3	45	0.681	65	0.451	80	0.583	73	0.591	79	0.618	73	0.190	75	0.534	73	0.982	37
2	46	0.974	25	0.723	53	0.876	34	0.769	62	0.788	56	0.200	73	0.626	58	0.675	77
3	47	.	.	0.987	23	1.000	1	1.000	1	1.000	1	0.286	59	0.622	60	0.814	54
2	48	0.730	53	0.656	62	0.743	56	0.898	38	0.897	43	0.207	69	0.603	65	0.677	75
1	49	0.954	28	0.822	40	1.000	1	0.741	68	.	.	.	.	.	.	.	.
1	50	.	.	1.000	1	0.664	65	1.000	1	1.000	1	1.000	1	0.434	77	0.916	44
2	51	0.694	63	0.545	73	0.641	68	1.000	1	1.000	1	0.280	60	0.869	32	1.000	1
1	52	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
3	53	0.970	26	0.524	74	0.541	76	0.681	73	0.684	66	0.154	79	0.615	62	0.746	63
3	54	0.715	57	0.823	39	0.895	32	0.750	67	0.764	58	0.073	89	0.692	52	0.683	74
3	55	1.000	1	0.998	22	1.000	1	1.000	1	1.000	1	0.126	82	0.707	50	1.000	1
3	56	.	.	0.768	46	0.762	54	0.857	50	0.912	37	0.318	54	.	.	.	.
3	57	0.967	27	0.907	31	0.814	46	0.946	33	0.911	38	0.326	52	0.570	70	0.796	57
2	58	0.701	60	0.481	77	0.562	74	0.567	80	0.544	78	0.416	45	0.514	75	0.531	86
3	59	0.695	62	1.000	1	0.919	29	0.724	70	0.936	35	0.294	57	0.642	55	0.741	64
3	60	0.702	59	0.648	63	0.799	50	0.808	57	.	.	.	.	0.571	69	0.660	78
1	61	1.000	1	0.904	32	0.748	55	0.886	43	0.761	59	0.571	35	0.782	40	0.938	43
2	62	.	.	.	.	0.475	78	0.754	66	0.522	79	0.539	39	1.000	1	1.000	1
1	63	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	0.929	21	1.000	1	1.000	1
3	64	0.760	50	0.828	38	0.899	31	0.759	65	0.809	55	0.116	84	0.933	27	0.999	35
1	65	0.771	48	0.730	51	0.951	27	1.000	1	0.857	47	0.967	20	0.903	29	0.913	45
1	66	0.760	50	0.611	67	0.596	72	0.769	62	0.618	73	0.595	33	1.000	1	1.000	1

Efficiency Scores & Ranks - DEA VRS cont'd

size	ID	2001		2002		2003		2004		2005		2006		2007		2008	
		efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank
2	67	1.000	1	.	.	0.743	56	.	.	.	.	.	.	.	.	1.000	1
1	68	1.000	1	0.676	59	0.950	28	0.950	31	.	.	.	.	.	.	.	.
2	69	0.865	35	0.752	49	.	.	.	.	.	.	0.291	58	.	.	0.885	46
1	70	0.603	74	0.752	49	.	.	0.810	56	0.841	48	0.578	34	0.787	39	0.831	50
1	71	0.679	66	0.981	24	0.827	44	0.763	64	0.688	64	0.401	47	0.631	57	0.590	85
3	72	.	.	0.768	46	0.836	41	1.000	1	0.969	31	0.145	80	.	.	1.000	1
3	73	.	.	0.698	57	0.836	41	0.854	53	0.823	51	0.207	69	.	.	1.000	1
3	74	0.910	32	0.886	35	0.856	38	0.774	61	0.687	65	0.098	86	.	.	0.752	62
2	75	0.838	39	0.645	64	0.707	62	0.685	72	0.627	71	0.428	44	0.617	61	0.702	71
1	76	1.000	1	1.000	1	0.602	70	0.887	41	.	.	0.697	27	.	.	.	.
3	77	0.905	33	0.937	29	.	.	.	.	.	.	.	.	.	.	.	.
2	78	0.688	64	0.783	45	0.788	51	0.852	54	0.814	53	0.389	49	.	.	1.000	1
2	79	0.621	72	0.428	82	.	.	.	.	0.872	46	0.161	76	.	.	0.676	76
1	80	0.768	49	0.791	43	.	.	.	.	0.633	70	0.483	41	.	.	0.634	81
2	81	0.939	29	0.877	36	1.000	1	0.831	55	.	.	1.000	1	.	.	1.000	1
3	82	0.707	58	0.480	78	0.835	43	0.894	39	1.000	1	0.193	74	1.000	1	0.863	48
1	83	.	.	.	.	.	.	.	.	.	.	0.739	25	.	.	1.000	1
2	84	0.699	61	.	.	.	.	.	.	0.732	62	0.201	72	.	.	0.804	56
1	85	1.000	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.
1	86	.	.	0.522	75	.	.	.	.	.	.	0.650	30	.	.	0.654	79
1	87	0.776	46	0.894	34	0.771	52	0.981	28	0.888	45	1.000	1	1.000	1	0.767	61
3	88	1.000	1	.	.	.	.	0.932	36	0.998	28	1.000	1	1.000	1	1.000	1
3	89	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	0.079	88	0.608	64	0.692	72
2	90	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
3	91	1.000	1	.	.	.	.	1.000	1	1.000	1	0.717	26	1.000	1	0.723	67
3	92	0.790	43	0.765	48	0.864	36	0.870	45	0.970	30	0.087	87	0.762	47	0.862	49
2	93	.	.	.	.	.	.	.	.	0.522	79	.	.	0.410	78	0.528	87
3	94	.	.	0.946	28	0.763	53	0.943	34	1.000	1	0.253	65	0.777	42	0.783	58
2	95	0.671	67	0.494	76	0.648	66	0.649	75	0.667	67	0.211	68	0.878	31	1.000	1
3	96	1.000	1	0.962	26	1.000	1	0.976	29	1.000	1	0.458	43	0.720	49	1.000	1
2	97	0.510	75	0.447	81	0.465	79	0.523	82	.	.	0.202	71	.	.	.	.
2	98	1.000	1	0.709	56	1.000	1	.	.	.	.	.	.	.	.	.	.
3	99	0.912	31	0.818	41	0.887	33	0.939	35	0.967	32	0.106	85	0.780	41	1.000	1

Table A.10: Efficiency Scores & Ranks - 2004 DEA vs. 2004 DEA TI

ID	CRS04 efficiency	CRS04 rank	VRS04 efficiency	VRS04 rank	CRS04_TI efficiency	CRS04_TI rank	VRS04_TI efficiency	VRS04_TI rank
1	.	.	.	.	.	.	.	.
2	0.635	21	0.856	51	0.682	25	0.949	43
3	0.416	66	0.515	83	0.425	67	0.592	79
4	0.635	21	0.870	45	0.635	30	0.892	48
5	0.615	26	0.617	77	0.962	13	0.974	38
6	0.485	57	0.560	81	0.485	60	0.560	82
7	0.516	54	0.784	60	0.516	57	0.785	67
8	0.231	82	0.608	78	0.231	82	0.709	74
9	0.578	36	1.000	1	0.578	42	1.000	1
10	0.631	23	0.870	45	0.651	28	0.998	36
11	0.602	29	1.000	1	0.602	35	1.000	1
12	1.000	1	1.000	1	1	1	1.000	1
13	0.967	8	1.000	1	0.967	12	1.000	1
14	1.000	1	1.000	1	1	1	1.000	1
15	.	.	.	.	.	.	.	.
16	0.622	24	1.000	1	0.622	31	1.000	1
17	0.393	71	1.000	1	0.857	15	1.000	1
18	0.480	60	1.000	1	0.48	63	1.000	1
19	0.771	12	1.000	1	1	1	1.000	1
20	0.567	37	0.883	44	1	1	1.000	1
21	0.593	32	0.917	37	0.787	19	1.000	1
22	0.612	27	0.856	51	0.65	29	0.856	58
23	0.203	83	1.000	1	0.203	83	1.000	1
24	1.000	1	1.000	1	1	1	1.000	1
25	0.318	78	1.000	1	0.318	78	1.000	1
26	0.410	67	0.504	84	0.41	68	0.504	84
27	0.520	53	0.714	71	0.557	44	0.716	73
28	0.538	48	0.894	39	0.538	52	0.894	47
29	1.000	1	1.000	1	1	1	1.000	1
30	0.477	61	0.736	69	0.604	34	0.862	56
31	0.582	34	0.887	41	0.582	41	0.887	49
32	0.655	20	0.950	31	0.655	27	1.000	1
33	0.590	33	0.974	30	0.59	39	0.974	38
34	1.000	1	1.000	1	1	1	1.000	1
35	0.235	81	0.790	59	0.235	81	0.835	61
36	0.657	19	0.665	74	0.993	11	1.000	1
37	0.579	35	1.000	1	0.598	38	1.000	1
38	0.540	46	0.863	49	0.54	50	0.863	55
39	.	.	.	.	.	.	.	.
40	.	.	.	.	.	.	.	.
41	0.384	73	0.630	76	0.384	73	0.630	78
42	0.409	68	0.868	48	0.409	69	0.868	53
43	0.526	52	0.806	58	0.526	56	0.806	66
44	0.744	15	1.000	1	0.744	22	1.000	1
45	0.406	69	0.591	79	0.406	70	0.591	80
46	0.555	41	0.769	62	0.555	46	0.769	68
47	0.699	18	1.000	1	0.699	24	1.000	1
48	0.545	44	0.898	38	0.545	48	0.944	45
49	0.741	16	0.741	68	1	1	1.000	1
50	0.460	62	1.000	1	0.827	17	1.000	1
51	0.550	42	1.000	1	0.59	39	1.000	1
52	1.000	1	1.000	1	1	1	1.000	1
53	0.432	64	0.681	73	0.432	65	0.681	76
54	0.279	79	0.750	67	0.279	79	0.767	70
55	0.602	29	1.000	1	0.602	35	1.000	1
56	0.532	50	0.857	50	0.532	54	0.857	57
57	0.545	44	0.946	33	0.545	48	0.946	44
58	0.431	65	0.567	80	0.431	66	0.567	81
59	0.508	55	0.724	70	0.508	58	0.724	72

Efficiency Scores & Ranks - 2004 DEA vs. 2004 DEA TI cont'd

ID	CRS04 efficiency	CRS04 rank	VRS04 efficiency	VRS04 rank	CRS04_TI efficiency	CRS04_TI rank	VRS04_TI efficiency	VRS04_TI rank
60	0.559	39	0.808	57	0.559	43	0.808	65
61	0.747	14	0.886	43	0.747	21	0.886	51
62	0.534	49	0.754	66	0.534	53	0.762	71
63	1.000	1	1.000	1	1	1	1.000	1
64	0.277	80	0.759	65	0.277	80	0.839	60
65	0.920	9	1.000	1	0.92	14	1.000	1
66	0.608	28	0.769	62	0.608	33	0.769	68
67	.	.	.	.	.	.	.	.
68	0.713	17	0.950	31	0.713	23	0.950	42
69	.	.	.	.	.	.	.	.
70	0.789	10	0.810	56	0.792	18	0.811	64
71	0.761	13	0.763	64	0.851	16	0.867	54
72	0.547	43	1.000	1	0.547	47	1.000	1
73	0.556	40	0.854	53	0.556	45	0.917	46
74	0.347	74	0.774	61	0.347	74	0.834	62
75	0.539	47	0.685	72	0.539	51	0.685	75
76	0.531	51	0.887	41	0.532	54	0.887	49
77	.	.	.	.	.	.	.	.
78	0.777	11	0.852	54	0.777	20	0.852	59
79	.	.	.	.	.	.	.	.
80	.	.	.	.	.	.	.	.
81	0.602	29	0.831	55	0.602	35	0.831	63
82	0.405	70	0.894	39	0.405	71	0.958	41
83	.	.	.	.	.	.	.	.
84	.	.	.	.	.	.	.	.
85	.	.	.	.	.	.	.	.
86	.	.	.	.	.	.	.	.
87	0.564	38	0.981	28	0.662	26	1.000	1
88	0.326	76	0.932	36	0.326	76	1.000	1
89	0.481	59	1.000	1	0.481	62	1.000	1
90	0.100	84	1.000	1	0.14	84	1.000	1
91	0.325	77	1.000	1	0.325	77	1.000	1
92	0.389	72	0.870	45	0.389	72	0.886	51
93	.	.	.	.	.	.	.	.
94	0.336	75	0.943	34	0.336	75	1.000	1
95	0.496	56	0.649	75	0.496	59	0.649	77
96	0.618	25	0.976	29	0.618	32	0.976	37
97	0.454	63	0.523	82	0.454	64	0.523	83
98	.	.	.	.	.	.	.	.
99	0.483	58	0.939	35	0.483	61	0.963	40
mean	0.569		0.860		0.607		0.889	
min	0.100		0.504		0.140		0.504	
max	1		1		1		1	
st.dev.	0.199		0.143		0.223		0.137	
no. obs.	84		84		84		84	
no. efficient	7		27		10		35	

Table A.11: Average Efficiency Scores & Ranks - without Determinants

Size	ID	CRS eff.	CRS rank	VRS eff.	VRS rank	SFA eff.	SFA rank	Size	ID	CRS eff.	CRS rank	VRS eff.	VRS rank	SFA eff.	SFA rank	Size	ID	CRS eff.	CRS rank	VRS eff.	VRS rank	SFA eff.	SFA rank
3	1	0.352	86	0.825	41	0.204	86	1	34	1.000	1	1.000	1	0.950	1	2	67	0.661	20	0.914	24	0.497	28
1	2	0.616	26	0.935	18	0.420	42	3	35	0.220	97	0.723	66	0.118	94	1	68	0.707	17	0.894	27	0.584	17
2	3	0.431	73	0.583	92	0.305	67	1	36	0.644	24	0.653	84	0.603	15	2	69	0.529	47	0.698	71	0.435	38
2	4	0.548	38	0.675	79	0.469	33	2	37	0.530	46	0.924	22	0.406	43	1	70	0.722	15	0.743	61	0.728	9
1	5	0.607	29	0.630	86	0.598	16	2	38	0.526	49	0.734	63	0.401	44	1	71	0.671	19	0.695	73	0.575	18
2	6	0.505	58	0.588	91	0.378	52	2	39	0.453	68	0.575	94	0.421	41	3	72	0.465	63	0.786	49	0.303	69
2	7	0.526	50	0.792	48	0.326	62	1	40	0.858	10	1.000	1	0.888	3	3	73	0.503	59	0.736	62	0.381	51
3	8	0.223	96	0.609	88	0.114	95	2	41	0.452	69	0.893	28	0.296	72	3	74	0.335	88	0.709	68	0.167	88
2	9	0.526	48	0.694	74	0.459	35	3	42	0.381	83	0.757	55	0.244	82	2	75	0.484	62	0.656	83	0.322	64
2	10	0.576	34	0.946	15	0.359	57	2	43	0.585	32	0.701	70	0.471	31	1	76	0.559	36	0.837	39	0.498	26
1	11	0.563	35	0.930	20	0.458	37	2	44	0.583	33	0.928	21	0.384	50	3	77	0.341	87	0.921	23	0.268	78
1	12	1.000	1	1.000	1	0.888	4	3	45	0.390	79	0.579	93	0.261	79	2	78	0.683	18	0.759	54	0.538	23
1	13	0.916	9	0.935	18	0.761	8	2	46	0.539	41	0.704	69	0.347	58	2	79	0.386	82	0.552	95	0.322	63
2	14	0.937	7	0.959	13	0.878	5	3	47	0.543	40	0.816	44	0.298	71	1	80	0.656	22	0.662	82	0.553	20
1	15	0.608	28	0.671	81	0.482	29	2	48	0.486	61	0.676	78	0.385	48	2	81	0.539	43	0.941	16	0.359	56
3	16	0.417	74	0.978	12	0.249	81	1	49	0.719	16	0.879	32	0.523	24	3	82	0.372	84	0.747	57	0.281	75
2	17	0.387	81	0.816	43	0.270	77	1	50	0.521	53	0.859	35	0.425	40	1	83	0.834	11	0.870	33	0.775	7
3	18	0.457	67	1.000	1	0.207	85	2	51	0.505	57	0.754	56	0.426	39	2	84	0.397	78	0.609	89	0.361	55
1	19	0.739	13	0.836	40	0.543	22	1	52	1.000	1	1.000	1	0.543	21	1	85	1.000	1	1.000	1	0.814	6
1	20	0.612	27	0.692	75	0.569	19	3	53	0.413	75	0.614	87	0.313	66	1	86	0.523	52	0.609	90	0.458	36
1	21	0.593	30	0.848	38	0.497	27	3	54	0.253	93	0.674	80	0.134	92	1	87	0.524	51	0.885	31	0.389	47
1	22	0.739	14	0.869	34	0.651	12	3	55	0.520	54	0.854	36	0.271	76	3	88	0.298	89	0.988	11	0.124	93
3	23	0.205	98	0.948	14	0.103	98	3	56	0.450	70	0.723	65	0.292	73	3	89	0.433	72	0.797	47	0.238	84
2	24	0.930	8	0.941	17	0.890	2	3	57	0.460	64	0.780	51	0.242	83	2	90	0.108	99	1.000	1	0.090	99
3	25	0.288	91	1.000	1	0.105	97	2	58	0.406	76	0.540	96	0.299	70	3	91	0.248	94	0.907	25	0.113	96
1	26	0.389	80	0.499	97	0.377	53	3	59	0.539	44	0.744	59	0.317	65	3	92	0.359	85	0.746	58	0.196	87
1	27	0.585	31	0.686	76	0.465	34	3	60	0.536	45	0.698	72	0.389	46	2	93	0.237	95	0.487	98	0.142	90
3	28	0.515	56	0.732	64	0.339	60	1	61	0.657	21	0.824	42	0.517	25	3	94	0.292	90	0.781	50	0.163	89
1	29	1.000	1	1.000	1	0.658	11	2	62	0.494	60	0.715	67	0.470	32	2	95	0.458	66	0.652	85	0.370	54
1	30	0.460	65	0.679	77	0.385	49	1	63	0.978	6	0.991	10	0.720	10	3	96	0.550	37	0.890	29	0.287	74
3	31	0.539	41	0.770	52	0.340	59	3	64	0.271	92	0.763	53	0.135	91	2	97	0.398	77	0.429	99	0.395	45
2	32	0.544	39	0.854	37	0.305	68	1	65	0.793	12	0.887	30	0.613	14	2	98	0.655	23	0.903	26	0.617	13
3	33	0.518	55	0.808	45	0.338	61	1	66	0.636	25	0.744	60	0.473	30	3	99	0.440	71	0.801	46	0.255	80

Table A.12: Efficiency Scores & Ranks - SFA with Determinants

size	ID	2001		2002		2003		2004		2005		2006		2007		2008	
		efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank	efficiency	rank
3	1	0.7732	66	0.7614	71	.	.	.	.	.	.	0.7897	73	0.7688	61	0.7638	71
1	2	0.9830	21	0.9820	21	0.9809	16	0.9797	23	0.9779	23	0.9840	13	0.9833	6	0.9818	14
2	3	0.9045	51	0.9028	49	0.8828	48	0.8689	53	0.8505	52	0.9152	41	0.9048	35	0.9039	38
2	4	0.9040	52	0.9077	43	0.8945	40	0.8925	45	0.8800	45	0.9291	34	0.9090	31	0.9093	35
1	5	0.9849	19	0.9846	15	0.9828	12	0.9820	19	0.9802	21	0.9842	12	0.9828	8	0.9826	9
2	6	0.9096	48	0.9022	50	0.8652	56	0.8488	60	0.8361	59	0.8895	48	0.8672	43	0.8722	49
2	7	0.8851	58	0.8680	61	0.8682	54	0.8566	57	0.8475	54	0.9118	43	0.9053	32	0.9059	37
3	8	0.5634	72	0.5458	78	0.5274	75	0.5138	78	0.5019	78	0.4859	84	0.4818	72	0.4773	82
2	9	0.8891	57	0.8920	56	0.8928	42	0.9433	31	0.9393	32	0.9178	40	0.9100	30	0.8993	39
2	10	0.9096	47	0.9043	47	0.8961	39	0.9433	32	0.9392	33	0.9248	36	0.9047	36	.	.
1	11	.	.	.	.	.	.	0.9868	8	0.9861	7	0.9843	11	0.9827	9	0.9823	10
1	12	.	.	0.9874	8	0.9863	8	0.9862	10	0.9853	11	0.9837	14	0.9819	11	.	.
1	13	0.9867	10	0.9879	7	0.9874	5	0.9869	7	0.9867	5	0.9861	6	0.9845	5	0.9837	6
2	14	0.9403	31	0.9491	29	0.9395	27	0.9600	27	0.9570	27	0.9521	30	0.9338	26	0.9293	31
1	15	0.9838	20	.	.	.	.	.	.	0.9823	19	0.9808	23	0.9786	19	0.9811	18
3	16	0.9286	38	0.8068	67	0.7948	65	0.7838	67	0.7553	67	0.8160	64	0.7762	58	0.7818	62
2	17	0.9225	42	0.8753	60	0.8658	55	0.8505	59	0.8332	61	0.8094	69	0.7796	54	0.7806	63
3	18	0.8806	59	0.8188	65	0.7958	64	0.7694	69	0.7468	68	0.8103	68	0.8244	48	0.7753	67
1	19	.	.	0.9884	5	0.9873	6	0.9866	9	0.9849	12	0.9833	16	0.9817	14	0.9815	15
1	20	0.9863	12	0.9832	18	0.9821	15	0.9794	24	0.9771	25	0.9753	28	0.9710	23	0.9712	26
1	21	0.9865	11	0.9824	20	0.9803	18	0.9782	26	0.9752	26	0.9820	20	0.9799	17	0.9809	19
1	22	0.9861	14	.	.	.	.	0.9785	25	0.9775	24	0.9745	29	0.9707	25	0.9711	27
3	23	0.9766	23	0.6580	75	0.6313	72	0.6071	76	0.5958	75	0.5665	81	0.5422	69	0.5378	79
2	24	0.7288	67	0.9660	26	0.9574	23	0.9528	29	0.9494	30	0.9245	37	0.9007	37	0.8947	41
3	25	.	.	0.6690	74	0.6387	71	0.6313	74	0.6087	74	0.5848	80	0.5608	68	0.5580	78
1	26	0.9884	6	.	.	.	.	0.9848	15	0.9837	17	0.9808	22	0.9786	20	0.9782	22
1	27	0.9455	28	0.9860	12	0.9835	10	0.9830	18	0.9823	18	0.9787	25	0.9751	21	0.9755	23
3	28	0.9884	5	0.9121	40	0.8924	44	0.8925	44	0.8849	43	0.8517	56	0.8159	52	0.8024	60
1	29	0.9899	3	0.9868	11	0.9860	9	0.9853	13	0.9844	15	0.9824	18	0.9797	18	0.9796	21
1	30	0.9550	27	0.9883	6	0.9877	4	0.9872	6	0.9861	8	0.9845	9	0.9821	10	0.9819	13
3	31	.	.	0.9220	35	0.9085	34	0.9085	39	0.8952	40	0.8633	51	0.8355	46	0.8307	57
2	32	.	.	.	.	0.9330	29	0.9255	35	0.9020	38	0.8762	49	0.8506	44	0.8544	50
3	33	.	.	.	.	0.9081	35	0.9026	41	0.8877	42	0.8531	54	0.8234	49	0.8319	56

Efficiency Scores & Ranks - SFA with Determinants cont'd

size	ID	2001 efficiency	2001 rank	2002 efficiency	2002 rank	2003 efficiency	2003 rank	2004 efficiency	2004 rank	2005 efficiency	2005 rank	2006 efficiency	2006 rank	2007 efficiency	2007 rank	2008 efficiency	2008 rank
1	34	.	.	.	.	.	.	0.9898	1	0.9891	1	0.9884	2	0.9873	1	0.9864	1
3	35	0.5932	71	0.5784	77	0.5619	74	0.5497	77	0.5326	77	0.5176	83	0.4968	71	0.4984	81
1	36	.	.	0.9841	17	0.9826	13	0.9810	22	0.9788	22	0.9755	27	0.9707	24	0.9727	25
2	37	0.9158	46	0.9095	42	0.8860	46	0.8877	47	0.8612	49	0.8372	59	0.8813	40	0.8917	42
2	38	.	.	0.9187	37	0.8975	37	0.8725	52	0.8505	53	0.8220	62	0.8853	39	0.8838	45
2	39	0.9263	39	.	.	.	.	.	.	0.8384	57	0.8411	58	0.8909	38	0.8811	46
1	40	.	.	.	.	.	.	.	.	0.9860	10	0.9899	1	0.9833	7	0.9826	8
2	41	.	.	0.9031	48	0.8740	52	0.8580	56	0.8527	51	0.8466	57	0.9048	34	0.9106	34
3	42	0.7870	64	0.7763	69	0.7495	67	0.7371	70	0.7260	70	0.7075	77	0.7635	62	0.7724	69
2	43	0.9371	34	0.9345	33	0.9228	31	0.9171	37	.	.	.	.	.	.	.	.
2	44	.	.	0.9600	27	0.9540	24	0.9519	30	0.9392	34	0.8923	47	0.8753	41	0.8728	48
3	45	0.8988	54	0.8960	53	0.8764	51	0.8627	54	0.8391	56	0.8076	70	0.7767	57	0.7780	65
2	46	0.9380	33	0.9379	32	0.9201	32	0.9075	40	0.8844	44	0.8523	55	0.8210	50	0.8028	59
3	47	.	.	0.9415	31	0.9337	28	0.9184	36	0.9017	39	0.8573	53	0.8177	51	0.8022	61
2	48	0.9418	30	0.9568	28	0.9517	25	0.9413	33	0.9309	37	0.9069	44	0.8708	42	0.8536	51
1	49	0.9851	18	0.9871	10	0.9863	7	0.9842	16	.	.	.	.	.	.	.	.
1	50	.	.	0.9912	1	0.9902	1	0.9895	3	0.9887	2	0.9879	3	0.9856	2	0.9849	3
2	51	0.9396	32	0.9324	34	0.9241	30	0.9152	38	0.8943	41	0.8651	50	0.8302	47	0.8360	54
1	52	0.9863	13	0.9851	14	0.9832	11	0.9814	21	0.9860	9	0.9843	10	0.9819	12	0.9821	11
3	53	0.9081	50	0.8937	54	0.8590	58	0.8519	58	0.8341	60	0.8105	67	0.7788	55	0.7767	66
3	54	0.6643	69	0.6437	76	0.6260	73	0.6125	75	0.5877	76	0.5593	82	0.5336	70	0.5284	80
3	55	0.9359	35	0.9195	36	0.9094	33	0.8944	43	0.8638	48	0.8137	65	0.7779	56	0.7733	68
3	56	.	.	0.8149	66	0.7977	63	0.7925	66	0.7738	66	0.7419	76	.	.	.	.
3	57	0.8501	62	0.7645	70	0.7446	68	0.7288	71	0.7061	71	0.6822	78	0.6534	65	0.6563	75
2	58	0.9301	37	0.8777	59	0.8507	60	0.8414	62	0.8203	62	0.7953	72	0.7723	59	0.7645	70
3	59	0.8989	53	0.9069	45	0.8592	57	0.8427	61	0.8374	58	0.8050	71	0.7690	60	0.7637	72
3	60	0.8922	56	0.8340	64	0.8135	62	0.8045	65	.	.	.	.	0.7240	64	0.7134	74
1	61	0.9861	15	0.9825	19	0.9804	17	0.9856	12	0.9848	14	0.9827	17	0.9817	13	0.9820	12
2	62	.	.	.	.	0.8723	53	0.9400	34	0.9345	36	0.9210	39	0.9051	33	0.8966	40
1	63	0.9880	9	0.9844	16	0.9826	14	0.9818	20	0.9812	20	0.9786	26	0.9749	22	0.9746	24
3	64	0.6109	70	0.5437	79	0.5235	76	0.5098	80	0.4962	80	0.4793	85	0.4644	74	0.4667	83
1	65	0.9855	17	0.9815	22	0.9795	19	0.9857	11	0.9848	13	0.9834	15	0.9815	15	0.9813	17
1	66	0.9856	16	0.9806	23	0.9791	20	0.9851	14	0.9837	16	0.9818	21	0.9807	16	0.9814	16

Efficiency Scores & Ranks - SFA with Determinants cont'd

size	ID	2001 efficiency	2001 rank	2002 efficiency	2002 rank	2003 efficiency	2003 rank	2004 efficiency	2004 rank	2005 efficiency	2005 rank	2006 efficiency	2006 rank	2007 efficiency	2007 rank	2008 efficiency	2008 rank
2	67	0.9712	24	.	.	0.9448	26	.	.	.	.	.	.	.	.	0.9421	28
1	68	0.9913	1	0.9901	2	0.9898	2	0.9896	2	.	.	.	.	.	.	.	.
2	69	0.9640	25	0.9490	30	.	.	.	.	.	.	0.9138	42	.	.	0.9367	29
1	70	0.9883	7	0.9873	9	.	.	0.9892	4	0.9885	3	0.9872	4	0.9850	4	0.9854	2
1	71	0.9881	8	0.9899	3	0.9889	3	0.9885	5	0.9874	4	0.9857	7	0.9852	3	0.9844	5
3	72	.	.	0.9017	51	0.8868	45	0.8821	49	0.8554	50	0.8272	61	.	.	0.8527	52
3	73	.	.	0.8922	55	0.8765	50	0.8598	55	0.8396	55	0.8200	63	.	.	0.8733	47
3	74	0.9357	36	0.8883	57	0.8517	59	0.8217	63	0.8040	64	0.7841	74	.	.	0.8411	53
2	75	0.9223	43	0.9186	38	0.8969	38	0.8977	42	0.9414	31	0.9294	33	0.9112	29	0.9132	33
1	76	0.9826	22	0.9805	24	0.9770	21	0.9833	17	.	.	0.9805	24	.	.	.	.
3	77	0.8674	60	0.8380	63	.	.	.	.	.	.	.	.	.	.	.	.
2	78	0.9259	40	0.9165	39	0.8932	41	0.8916	46	0.8677	46	0.8372	60	.	.	0.8088	58
2	79	0.9188	44	0.9000	52	.	.	.	.	0.9348	35	0.9062	45	.	.	0.8870	44
1	80	0.9904	2	0.9891	4	.	.	.	.	0.9864	6	0.9853	8	.	.	0.9828	7
2	81	0.8931	55	0.8866	58	0.8794	49	0.8781	50	.	.	0.9230	38	.	.	0.8911	43
3	82	0.7751	65	0.7603	72	0.7381	69	0.7251	72	0.8095	63	0.7639	75	0.7616	63	0.7374	73
1	83	.	.	.	.	.	.	.	.	.	.	0.9822	19	.	.	0.9798	20
2	84	0.9430	29	.	.	.	.	.	.	0.9542	28	0.9445	31	.	.	0.9340	30
1	85	0.9892	4	.	.	.	.	.	.	.	.	.	.	.	.	.	.
1	86	.	.	0.9851	13	.	.	.	.	.	.	0.9864	5	.	.	0.9848	4
1	87	0.9587	26	0.9661	25	0.9622	22	0.9567	28	0.9513	29	0.9358	32	0.9313	27	0.9201	32
3	88	0.5152	74	.	.	.	.	0.4958	81	0.4845	82	0.4732	86	0.4674	73	0.4589	84
3	89	0.5143	75	0.5336	80	0.5099	77	0.4948	82	0.4866	81	0.4493	90	0.4455	78	0.4404	88
2	90	0.6819	68	0.7186	73	0.6907	70	0.6691	73	0.6446	73	0.6285	79	0.6188	67	0.6306	77
3	91	0.5280	73	.	.	.	.	0.5127	79	0.4963	79	0.4655	87	0.4590	75	0.4486	85
3	92	0.4981	76	0.5158	81	0.4999	78	0.4851	84	0.4741	84	0.4559	88	0.4505	76	0.4411	86
2	93	.	.	.	.	.	.	.	.	0.6820	72	.	.	0.6495	66	0.6408	76
3	94	.	.	0.5156	82	0.4761	79	0.4861	83	0.4777	83	0.4556	89	0.4480	77	0.4409	87
2	95	0.9161	45	0.9099	41	0.8928	43	0.8866	48	0.8649	47	0.9260	35	0.9124	28	0.9071	36
3	96	0.8648	61	0.8426	62	0.8163	61	0.8055	64	0.7802	65	0.8591	52	0.8377	45	0.8327	55
2	97	0.9089	49	0.9060	46	0.8848	47	0.8736	51	.	.	0.9028	46	.	.	.	.
2	98	0.9256	41	0.9069	44	0.9011	36	.	.	.	.	.	.	.	.	.	.
3	99	0.7941	63	0.8055	68	0.7788	66	0.7698	68	0.7458	69	0.8116	66	0.7847	53	0.7792	64

Table A.13: Average Efficiency Scores & Ranks
- SFA with & without Determinants

Size	ID	SFA eff.	SFA rank	SFA_det eff	SFA_det rank	Size	ID	SFA eff.	SFA rank	SFA_det eff	SFA_det rank
3	1	0.204	86	0.771	83	2	51	0.426	39	0.892	51
1	2	0.420	42	0.982	23	1	52	0.543	21	0.984	16
2	3	0.305	67	0.892	53	3	53	0.313	66	0.839	74
2	4	0.469	33	0.903	48	3	54	0.134	92	0.594	91
1	5	0.598	16	0.983	18	3	55	0.271	76	0.861	68
2	6	0.378	52	0.874	65	3	56	0.292	73	0.784	81
2	7	0.326	62	0.881	58	3	57	0.242	83	0.723	86
3	8	0.114	95	0.512	93	2	58	0.299	70	0.832	76
2	9	0.459	35	0.910	45	3	59	0.317	65	0.835	75
2	10	0.359	57	0.917	41	3	60	0.389	46	0.797	80
1	11	0.458	37	0.984	14	1	61	0.517	25	0.983	17
1	12	0.888	4	0.985	12	2	62	0.470	32	0.912	43
1	13	0.761	8	0.986	8	1	63	0.720	10	0.981	26
2	14	0.878	5	0.945	35	3	64	0.135	91	0.512	94
1	15	0.482	29	0.981	24	1	65	0.613	14	0.983	19
3	16	0.249	81	0.805	78	1	66	0.473	30	0.982	21
2	17	0.270	77	0.840	73	2	67	0.497	28	0.953	33
3	18	0.207	85	0.803	79	1	68	0.584	17	0.990	1
1	19	0.543	22	0.985	13	2	69	0.435	38	0.941	37
1	20	0.569	19	0.978	29	1	70	0.728	9	0.987	5
1	21	0.497	27	0.981	28	1	71	0.575	18	0.987	6
1	22	0.651	12	0.976	31	3	72	0.303	69	0.868	67
3	23	0.103	98	0.639	89	3	73	0.381	51	0.860	69
2	24	0.890	2	0.909	47	3	74	0.167	88	0.847	71
3	25	0.105	97	0.607	90	2	75	0.322	64	0.916	42
1	26	0.377	53	0.982	20	1	76	0.498	26	0.981	27
1	27	0.465	34	0.976	32	3	77	0.268	78	0.853	70
3	28	0.339	60	0.880	60	2	78	0.538	23	0.877	62
1	29	0.658	11	0.984	15	2	79	0.322	63	0.909	46
1	30	0.385	49	0.982	22	1	80	0.553	20	0.987	7
3	31	0.340	59	0.881	59	2	81	0.359	56	0.892	52
2	32	0.305	68	0.890	54	3	82	0.281	75	0.759	84
3	33	0.338	61	0.868	66	1	83	0.775	7	0.981	25
1	34	0.950	1	0.988	4	2	84	0.361	55	0.944	36
3	35	0.118	94	0.541	92	1	85	0.814	6	0.989	2
1	36	0.603	15	0.978	30	1	86	0.458	36	0.985	11
2	37	0.406	43	0.884	55	1	87	0.389	47	0.948	34
2	38	0.401	44	0.876	63	3	88	0.124	93	0.483	97
2	39	0.421	41	0.876	64	3	89	0.238	84	0.484	96
1	40	0.888	3	0.985	10	2	90	0.090	99	0.660	87
2	41	0.296	72	0.879	61	3	91	0.113	96	0.485	95
3	42	0.244	82	0.752	85	3	92	0.196	87	0.478	98
2	43	0.471	31	0.928	38	2	93	0.142	90	0.657	88
2	44	0.384	50	0.921	39	3	94	0.163	89	0.471	99
3	45	0.261	79	0.842	72	2	95	0.370	54	0.902	49
2	46	0.347	58	0.883	56	3	96	0.287	74	0.830	77
3	47	0.298	71	0.882	57	2	97	0.395	45	0.895	50
2	48	0.385	48	0.919	40	2	98	0.617	13	0.911	44
1	49	0.523	24	0.986	9	3	99	0.255	80	0.784	82
1	50	0.425	40	0.988	3						

Appendix B

IES Working Paper 2/2011

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Efficiency of Hospitals in the Czech Republic

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IES Working Paper: 2/2011

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Efficiency of Hospitals in the Czech Republic

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Abstract:
The paper estimates cost efficiency of 99 general hospitals in the Czech Republic during 2001-2008 using Stochastic Frontier Analysis. We estimate a baseline model and also a model accounting for various inefficiency determinants. Group-specific inefficiency is present even having taken care of a number of characteristics. We found that inefficiency increases with teaching status, more than 20,000 treated patients a year, not-for-profit status and a larger share of the elderly in the municipality. Inefficiency decreases with less than 10,000 patients treated a year, larger population, and more hospitals in the region.

Keywords: Efficiency, hospitals, stochastic frontier analysis.

JEL: D24, I11

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1 Introduction

Tightening budget and increasing pressures on the efficiency of public spending represent currently major challenges for the Czech government. Health care provision is not an exception. Public financing of health care in the Czech Republic is still enormous. Out of 250,802 million CZK which was expended on health care in 2008, general government expenditure amounted to 84.7%.[1] Debates about inefficiency of the Czech health care system have resulted in a number of reforms. The major ones include increasing private involvement on health care funding and privatization of hospitals. Indicators of relative efficiency are thus necessary to gauge whether the cost-containment efforts were successful.

The first empirical literature on measuring efficiency of hospitals appeared in 1980s, examples include Nunamaker (1983) or Sherman (1984) who estimated efficiency of US hospitals. However, their primary purpose was to test the appropriateness of frontier models to be used in the sphere of health care. Since 1990s measuring efficiency of hospitals as well as examining its determinants has been a major interest of health care economics all around the world. A number of studies analyzed US data, such as Zuckerman *et al.* (1994), Rosko & Chilingerian (1999), Vitaliano & Toren (1996), or Rosko (2001). In Europe, Wagstaff & Lopez (1996) and Prior (1996) analyzed efficiency of Spanish hospitals. Magnussen (1996) analyzed Norwegian hospitals. Efficiency analysis of hospital sector spread to many other countries after 2000. These include Austrian hospitals in Hofmarcher *et al.* (2002), Swiss hospitals in Farsi & Filippini (2004) or British hospitals in Jacobs (2001). The list is not exhaustive, more examples can be found in Worthington (2004) or Hollingsworth (2008) who provide an overview of empirical studies dealing with hospital efficiency measurement, the latter of which is updated on regular basis.

Individual efficiency scores are dependent on the characteristic features of each unit examined. When not accounted for, lower efficiency scores are taken as inefficiency even though caused by the environmental factors. Factors which may influence inefficiency of a hospital include size, ownership type, or location. Zuckerman *et al.* (1994) is considered to be a pioneering work in the examination of determinants of inefficiency, later further studies emerged (e.g. Rosko & Chilingerian, 1999; Rosko, 2001; Folland & Hofler, 2001).

The high number of empirical studies dealing with hospital efficiency and its determinants abroad supports the necessity to deal with the subject matter. Unfortunately, a similar analysis of hospital efficiency is scarce or even missing in former Communist countries including the Czech Republic. An analysis of efficiency of hospitals in the Czech Republic has been carried out only in Dlouhý *et al.* (2007) so far. They estimated technical efficiency of a cross-sectional sample of 22 Czech hospitals in 2003 using a non–parametric approach (Data Envelopment Analysis). Not only was the sample quite small, but no effect of environmental factors on inefficiency was taken into account. The small sample size is likely to bias the frontier. In other words, when an efficient observation is not included, the frontier shifts down and originally inefficient observations are considered efficient. Moreover, when determinants of inefficiency are not taken care of, low efficiency scores might be wrongly considered as inefficiency even

[1] http://www.oecdilibrary.org/oecd/content/table/20758480-table3

though caused by the environment-specific factors. Furthermore, limitations of the method employed in Dlouhý *et al.* (2007) stem from the fact that the entire deviation is regarded as inefficiency and no statistical noise is taken care of. Parametric and non-parametric approaches should thus complement each other in order to provide an overall picture of efficiency of Czech hospitals.

Our analysis contributes to the field of missing research. In order to measure efficiency of Czech hospitals, we employ Stochastic Frontier Analysis, a parametric method that aims to envelop the data such that the level of inefficiency of individual units is revealed. We analyze efficiency firstly without determinants, consequently employ potential determinants of inefficiency in an additional analysis and compare the results. We try to answer the following questions: (i) how efficient Czech hospitals are under SFA with and without determinants; (ii) which exogenous environmental factors, such as hospital status or geographical setting, influence the estimated inefficiency scores and what effect they have; (iii) how much individual efficiencies differ in terms of ranking with and without determinants.

The paper analyzes 99 Czech hospitals in the period 2001–2008; only general hospitals are subject of the analysis. We estimate a Cobb-Douglas cost function in which total inpatient cost adjusted for inflation is used as the dependent variable. Inpatient days, doctor/bed and nurse/bed ratios and salaries are used as independent variables. A means to account for severity of cases in inpatient days was developed. The paper analyzes the effect of various determinants of inefficiency—size of the hospital according to patients treated, for-profit/not-for-profit status, teaching status, population size and share of the elderly in the municipality where the hospital is situated, as well as the number of hospitals in the region. All determinants proved to have a significant effect on inefficiency. Teaching status increases inefficiency of Czech hospitals since additional costs are expected to be incurred. Small hospitals tend to be more efficient than big hospitals; hospitals with for-profit status are more efficient, as well as hospitals in bigger cities. However, larger share of elderly people makes hospitals less efficient. Larger number of hospitals in the region seems to put pressure on hospitals to increase their efficiency.

This paper is organized as follows. Section 2 provides theoretical background for efficiency analysis and describes the estimation methodology. Section 3 presents the dataset and introduces variables employed. Section 4 presents results of the efficiency estimation without and with determinants, respectively. Effects of determinants on inefficiency are analyzed and efficiency scores obtained under both methods are discussed. Section 5 concludes and provides motivation for further research.

2 Methodology

The purpose of efficiency measurement is to find the maximum feasible amount of output which can be obtained from a given set of input. A number of techniques to estimate efficiency have been developed over past 40 years. The most widely applied approaches are frontier techniques. These determine the distance of an individual observation from the efficiency frontier. Such a frontier is formed from fully efficient observations from the data set, i.e.

those which employ inputs utmost economically.

The pioneering method of efficiency measurement in the work of Farrell (1957) dealt with *technical efficiency*. Such a method employs inputs and outputs in physical units without the requirement on any price information. It states that if an organization is technically efficient, it is placed on the frontier. Farrell's concept was enriched by Charnes *et al.* (1978) who introduced the concept of *allocative efficiency* stating that even if an observation is placed on the frontier (from Farrell's perspective), allocative inefficiency is present if it uses a mix of inputs in suboptimal proportions given their respective prices and available technology. Technical and allocative efficiently together represent the overall *economic efficiency*.

Depending on the purpose of the study, efficiency can be measured as input or output-oriented. In the *input orientation*, under a given level of output, observations are compared in terms of input minimization, while in the *output orientation*, input is given but output maximized. In other words, if an observation, a Decision Making Unit (further 'DMU') as called in the frontier literature, is placed on the frontier, it produces the same amount of output employing less input than other DMUs below the frontier or, alternatively, it produces more output for a given level of input. Whether input or output orientation is selected depends to a large extent on what managers of the particular set of DMUs have most control over (Coelli, 1996a, p. 23). A majority of studies in the health care sector have applied input-oriented models since the DMUs have usually a certain level of output exogenously set, for they respond to the demands from the community (Zuckerman *et al.*, 1994; Yong & Harris, 1999; Vitaliano & Toren, 1996; Kontodimopoulos *et al.*, 2006).

Frontier techniques may be divided into parametric and non-parametric; deterministic and stochastic approaches. *Parametric methods*, aim at determining efficiency of an organization against some idealized benchmark, while *non-parametric methods* evaluate efficiency of an organization relative to other DMUs in the set. The parametric method requires that the cost function be specified in order for the efficiency frontier to be formed. There is no such requirement in non-parametric methods. These instead employ data in natural units.

Deterministic and stochastic approaches differ in the attitude to the error term. *Deterministic methods* assume that the entire deviation from the frontier is caused by inefficiency. On the contrary, *stochastic approaches* acknowledge that the deviation from the frontier is composed of two parts, one representing inefficiency and the other randomness. That is to say, the stochastic frontier approach acknowledges external factors which may include differences in uncontrollables directly connected with the production function, i.e. operating environments; or econometric errors, i.e. misspecification of the production function and measurement errors. It implies therefore that when using a deterministic approach, no observation can lie above the efficient set, however, this must not necessarily be the case with the stochastic approach since randomness can shift the DMU concerned above or below the efficiency frontier.

2.1 Stochastic Frontier Analysis

When estimating efficiency of hospitals in the Czech Republic, *Stochastic Frontier Analysis* was employed (further 'SFA'). It is a stochastic benchmarking parametric technique, the cross-sectional variant of which was first proposed by Aigner *et al.* (1977) and Meeusen &

van den Broeck (1977) independent of each other.

The model is specified as a cost function. Cost function is more convenient to be used in health care applications and thus such a specification was also often encountered in the literature, such as Rosko (2001); Rosko & Chilingerian (1999); Wagstaff & Lopez (1996); Jacobs (2001); Yong & Harris (1999); Chirikos & Sear (2000); Frohloff (2007); Zuckerman *et al.* (1994). The function takes a Cobb-Douglas form:[2]

$$\ln c_{it} = \beta_0 + \sum_{s=1}^{S} \beta_s \ln y_{it}^s + \sum_{m=1}^{M} \beta_m \ln w_{it}^m, \tag{1}$$

where c_{it} corresponds to total costs for DMU_i, $i \in N$, $N = (1, \ldots, n)$, at time $t \in T$, $y^1, \ldots, y^s$ are output variables and $w^1, \ldots, w^m$ denote input prices.

Two models will be used to analyze hospitals in the Czech Republic. Firstly, when only data on output and input prices will be analyzed without accounting for heterogeneity, the panel data version of the cost function will take the following form (Battese & Coelli, 1992):

$$c_{it} = f(\mathbf{y}_{it}, \mathbf{w}_{it}, \beta) + v_{it} + u_{it} \tag{2}$$

where $\mathbf{y}_{it}$ is a $s \times 1$ vector of outputs of DMU_i at time t; $\mathbf{w}_{it}$ is a $m \times 1$ vector of input prices and β is a vector of unknown parameters to be estimated. v_{it} is a random variable which is assumed to be i.i.d., $v_{it} \sim N(0, \sigma_v^2)$ and independent of u_{it}. The inefficiency effect u_{it} is expressed as

$$u_{it} = u_i \exp(-\eta(t - T)), \tag{3}$$

where u_i are non-negative random variables assumed to be independent identically distributed as truncation at zero of the $u_i \sim N(\mu, \sigma_u^2)$ distribution; parameter η allows for time-varying inefficiency and represents a parameter to be estimated.

Secondly, we will take advantage of the model developed by Battese & Coelli (1995). It is primarily useful when efficiency determinants are analyzed since this model can accommodate determinants of inefficiency directly in one-step estimation.[3] The model looks as in (2), except, the inefficiency effect is specified as

$$u_{it} = \delta \mathbf{z}_{it} + \omega_{it}, \tag{4}$$

where $\mathbf{z}_{it}$ is a $1 \times p$ vector of determinants of inefficiency of DMU_i at time t, δ is a vector of parameters to be estimated, ω_{it} is a random variable defined by truncation of the normal

[2] A Translog specification was also considered but based on the results, it proved inappropriate.

[3] There are a number of other methods to account for heterogeneity. The simplest possibility includes dividing the sample according to the criterion of interest as in Zuckerman *et al.* (1994), Nayar & Ozcan (2008) or Hofmarcher *et al.* (2002). However, efficiency scores cannot be compared across groups since each sample set has a different reference point. Furthermore, if the sample size is small the analysis is jeopardized. The second possibility comprises a two-stage approach, where efficiency scores from the first stage are regressed on a set of possible determinants, nevertheless, the possibility of bias due to 'left out variables' arises as an immediate objection. As Greene (2003) puts it "if such covariates do have explanatory power, then they should appear in the model at the first step". Moreover, the distributional assumptions used in the first and second steps contradict each other as explained by Coelli *et al.* (2005).

distribution with zero mean and variance σ^2, such that the truncation point is $-\delta \mathbf{z}_{it}$, i.e. $\omega_{it} \geq -\delta \mathbf{z}_{it}$. u_{it} is thus of non-negative truncation of the $N(\delta \mathbf{z}_{it}, \sigma^2)$ distribution. In other words, determinants of inefficiency influence the mean of the truncated normal distribution. It results, that if all the elements of the δ-vector are equal to zero, the inefficiency effects are not related to the z-variables and a half-normal distribution (with zero mean) is obtained.

Since the above formulated SFA models will be estimated using maximum likelihood, a parametrization similar to Battese & Corra (1977) will become useful. It creates a joint density function for both inefficiency and the random noise and replaces σ_v^2 and σ_u^2 with $\sigma^2 = \sigma_v^2 + \sigma_u^2$. At the same time parameter γ is identified such that

$$\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)}.$$

Basically, SFA estimation of inefficiency in a panel relies upon the unobservable u_{it} being predicted. It is obtained as a conditional expectation of u_{it} upon the observed value. Using maximum likelihood[4], only

$$\epsilon_{it} = v_{it} + u_{it} = y_{it} - \beta x_{it} \tag{5}$$

can be directly observed. Consequently, time and DMU-specific inefficiency u_{it} is conditioned upon the observed overall residual as in Jondrow *et al.* (1982) or Battese & Coelli (1988):

$$E[u_{it}|\epsilon_{it}] = \frac{\sigma\lambda}{1+\lambda^2}\Big[\frac{\phi(a_{it})}{1-\Phi(a_{it})} - a_{it}\Big], \tag{6}$$

where $\lambda = \frac{\sigma_u}{\sigma_v}$; $a_{it} = \pm\frac{\epsilon_{it}\lambda}{\sigma}$; $\phi(a_{it})$ is the standard normal density evaluated at a_{it}; $\Phi(a_{it})$ is the standard normal cumulative distribution function evaluated at a_{it}.

3 Data

Panel data on 99 general hospitals in the Czech Republic for the period of 2001–2008 was analyzed. From 140 Czech hospitals initially considered, 30% was excluded for various reasons. Some of them were closed, incorporated into larger systems or transformed, and some hospitals did not report data for certain years.The final unbalanced panel consists of 661 observation. The number of observations in each cross-section varies from 76 in 2001 to 90 in 2006. The list of hospitals analyzed in this paper is provided in Table A1. Most of the hospitals treat up to 20,000 patients a year on average. There are two very big hospitals in the sample treating more than 70,000 patients a year. The third biggest hospital cures 'only' 54,700 patients a year. The distribution of hospitals in terms of size is depicted in Figure 1.

The data on individual hospitals was obtained from the Institute of Health Information and Statistics of the Czech Republic (further 'UZIS'),[5] specifically from the following two publications: 'Healthcare - Regions and the Czech Republic' ('Zdravotnictví kraje + ČR') for individual years and 'Operational and Economic Information on Inpatient Facilities in

[4]Subject to some sign changes, the log likelihood function of the cost function is to be found in Battese & Coelli (1992).

[5]www.uzis.cz

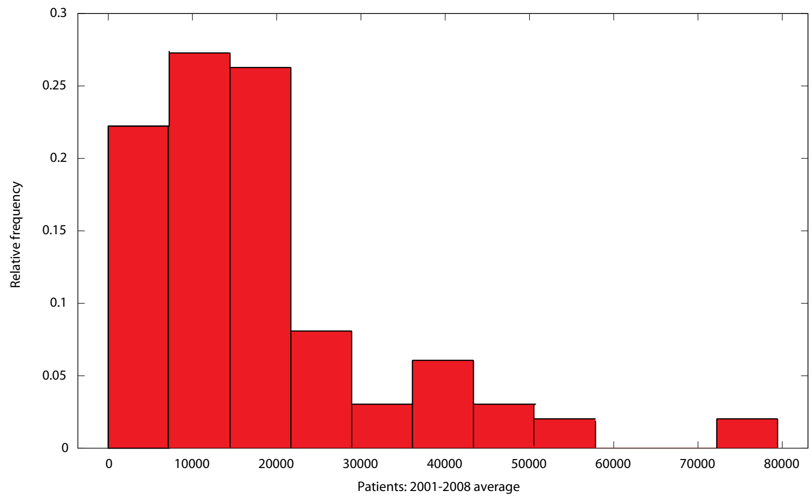

Figure 1. Size distribution of hospitals

Regions' ('Provozně-ekonomické informace lůžkových zařízení v ... kraji'). Most of the data used as determinants of inefficiency was obtained from the Czech Statistical Office, Regional Yearbooks. Data concerning ownership and profit status was obtained from the Registry of Companies in the Czech Republic.[6] Data expressed in monetary terms, i.e. costs and salaries, was adjusted for inflation using annual growth rate of inflation with 2001 representing the base year.

Efficiency was estimated with Coelli *et al.*'s SFA software *FRONTIER Version 4.1.* (Coelli, 1996b). For general analysis statistical softwares R 2.8.1 (R Development Core Team, 2006) and Gretl (Cottrell & Lucchetti, 2007) were used.

3.1 Cost function

Since we estimate a cost function and thus measure cost efficiency, the dependent variable is represented by total operating costs (denoted as 'costs' in the analysis), these include all inpatient costs, but exclude capital costs. It was calculated as multiplication of operating costs per patient day, the number of admissions and the average length of stay, all of which are available from UZIS. UZIS calculates operating costs per patient day as:

$$L\frac{1+\frac{D+J+N}{L+A}}{T},$$

where L are costs for inpatient care, D costs for medical transport, J costs for other medical care, N costs for non-medical procedures, A outpatient costs and T number of inpatient days.

UZIS acknowledges that this method to obtain operating costs per patient day is not absolutely accurate from the economic point of view. However, it suffices for the purposes of this paper since inpatient costs are not obtainable otherwise. Furthermore, since the

[6] www.obchodnirejstrik.cz.

calculation method is the same for all hospitals, using this data should not result in major difficulties.

Ideally, health output should be measured as an increment to patient health status, i.e. as final products of hospitals. However, since this is technically impossible to measure, in all hospital efficiency studies intermediate outputs of various kinds are used instead. In this paper, only output from inpatient care is considered. Not only was data on complete output not available but Yong & Harris (1999) also found out that inpatient care consumes majority of hospital resources. These findings are supported by the data on economic information provided from UZIS (2005), which disaggregate hospital costs into inpatient, outpatient, transport costs and non-medical expenses. Inpatient costs of Czech hospitals are around 50% of total costs on average. Of the remaining categories, outpatient care accounts for between 15–20% of total costs, the rest is taken up by transportation costs and non-medical expenses. One should also keep in mind in this context that total operating costs, which is used as dependent variable, refers to inpatient care only. Because of all these reasons, employing inpatient care exclusively is absolutely appropriate.

In the studies mentioned above, inpatient output was approximated either by the number of admissions, i.e. number of patients treated, or the number of inpatient days. Some discussion and controversies appear on which of these two variables should be preferable. Specifically, Zuckerman *et al.* (1994), Farsi & Filippini (2004) and Hofmarcher *et al.* (2002) suggest that the number of patients should rather be employed due to possible endogeneity in the number of patient days. In other words, the length of stay, which to a certain extent reflects how patients are treated, is in the direct control of the hospital, and thus the inefficiencies of production function are transferred into output and thus are likely to be correlated with the inefficiency term of the cost function. On the other hand, Magnussen (1996) points out that the number of inpatient days is assumed to be better since they are "a more medically homogeneous units" (Magnussen, 1996, p. 30). Additionally, the length of stay could be connected with the complexity of the cases treated as well as differences in management, aspects which the number of patients specification would not take account of.

Based on the discussion, we assume that endogeneity is rather unlikely in the Czech Republic since hospitals are place-constrained rather than deciding on the length of stay themselves and thus transferring inefficiency into their production function. Moreover, in the context of Czech hospitals competition in health care coverage does not work and thus hospitals do not choose among patients with shorter or longer length of stay in order to influence their efficiency. Moreover, the correlation of the inpatient days and the number of patients is considerably high. Therefore, only inpatient days are used here.

Furthermore, as claimed by Rosko & Chilingerian (1999), Valdmanis (1992) and Hofmarcher *et al.* (2002), weighting according to severity of cases is absolutely vital for the efficiency analysis.[7] We will weight the number of patient days according to the case-mix criteria as of UZIS (2005) publications, which disaggregates total inpatient days into non-operative wards (*non_op_days*), operative wards (*op_days*), intensive care (*intense_days*) and

[7] Magnussen (1996) proved that the choice of weighting criteria has an effect on the resulting individual efficiency scores and ranks.

nursing care/long-term care (*nursing_days*).[8] We, however, distinguish only among nursing days and total number of non-operative, operative and intensive-care days (*sum_3_days*). In the preliminary analysis below, we provide reasons for summing up these three types of care.

Besides the weighted number of patient days, there are other variables expected to play a role. These include for instance indicators of the quality of care, which will also be included into the analysis as output variables. Specifically, quality of care is likely to increase costs of hospitals, however at the same time, output of higher quality can be considered as more output. Quality of care was accounted for differently in the literature. For instance Zuckerman *et al.* (1994) included mortality rates. Vitaliano & Toren (1996) employed technology index and occupancy rate, which is defined as a ratio of the actual patient days to the maximum patient days possible. If there is excess capacity in a hospital, an admitted patient is likely to be put into a separate room and thus is provided with a higher quality care. Moreover, doctors devote more of their time and effort to each patient. Unfortunately, the inclusion of this variable here was hampered by its correlation with patient days. Quality of care variables used in this paper will comprise per day doctor/bed and nurse/bed ratios (*doctor_bed, nurse_bed*) as in Frohloff (2007). These ratios were calculated from the data from UZIS. Basically, the more doctors/nurses attend one bed per day, the higher the quality of care is assumed to be.

To complete the cost function, input prices were included. These however represent wages (*salary*) only, price of capital was left out, because of past empirical applications where capital cost is deemed imperceptible and thus is neglected. Price of labor was proxied by average monthly wages for districts. Although wages of doctors and nurses are partly given by tariffs, prices of services and goods related to inpatient care purchased by a hospital reflect expensiveness of the region. The Czech Statistical Office provides data only till 2004. From 2005 on, data is not statistically collected anymore and only regional information is available. Therefore, for the remaining years, i.e. 2005–2008, information from 2004 was adjusted for annual growth of the average wage in the region. This approximation is considered to be sufficient for the analysis. The data was adjusted for inflation with 2001 representing the base year.

3.2 Determinants of inefficiency

A set of variables usually explains some portion of inefficiency. The choice of variables used as potential determinants in this paper has been guided by empirical studies in the sphere of health care and data availability.

Teaching hospitals (*teaching*) tend to reveal a different structure of services providing less of basic and more of highly specialized care, management and organization of resources. (Vitaliano & Toren, 1996, p. 165). Therefore, the presence of teaching status has been acknowledged as a very important determinant of efficiency.

[8] Information on disaggregation is available also for 2004, however it slightly differs dividing inpatient days into basic care, specialized care, intensive care and nursing/long-term care. Share of intensive care and nursing/long-term care, the two categories which were kept the same in both years were found to be considerably stable, (share of intensive care with correlation of 0.98, nursing care was correlated by 0.85 between 2004 and 2005).

Hospitals in the sample were divided into three groups according to size since it is assumed that being of certain size might reveal some economies or diseconomies of scale and thus influence efficiency. The logics behind is consistent with Farsi & Filippini (2004). The number of beds and the number of treated patients were found to be correlated by 0.98. Therefore, division according to either of the categories does not make much difference. In this paper, hospitals were divided according to the number of patients treated to small hospitals (below 10,000, *size1*), medium hospitals (10,000–20,000, *size2*) and big hospitals (above 20,000, *size3*). All the groups contain equally 33 observations. Only the effect of small and big hospitals in the sample will be studied.

According to the economies of scale rationale, one would expect that efficiency of a hospital increases with its size. This hypothesis was proved by Zuckerman *et al.* (1994) and Vitaliano & Toren (1996). On the other hand, using available beds to account for size, Yong & Harris (1999) found out that it decreases efficiency. Yong & Harris's findings could be explained by the presence of other costs to manage complexity of a larger scale practice, such as professional administration, information technology demands, infrastructure, etc. The mixed empirical findings, suggest that size effect is region-specific. Therefore, either of the effects might result, i.e. that size decreases inefficiency due to economies of scale effect, or, that size increases inefficiency due to increased costs connected with the management of complex care.

Keeping in mind transformation of many of the Czech hospitals into joint stock companies starting in 2004, ownership is expected to explain a significant portion of inefficiency because the main purpose of privatization was to curb costs and increase efficiency. It is interesting to point out that many of the hospitals which were transformed anytime during the period examined, changed their status in 2006, 23 out of 41. Additionally, even though many Czech hospitals have been transformed into joint-stock companies, regions, district or municipalities are their major shareholders. Therefore, they are still to a large extent publicly owned.

Having carefully examined individual hospitals, it has been found that only 5% of for-profit hospitals are owned by a private entity. Hence, it is hard to uncover the effect of ownership (private versus public) for for-profit hospitals. Therefore, we aim to find effects of the not-for-profit status (*not_profit*), when effects of for-profit hospitals (95% of them are public) are compared to public not-for-profit hospitals. The hypothesis is that not-for-profit public status has a positive effect on inefficiency.

The remaining determinants express attributes of the environment in which the hospital is situated rather than of the hospital itself. Population size (*population*) is expected to affect inefficiency. Data on population was gathered for municipalities where hospitals are situated. Prague was taken as one municipality and thus its population was expected to bias the results, therefore, the population of Prague was divided into core catchment areas of individual hospitals. Specifically, the total population of Prague was split according to the share of patients treated in each of the Prague's general hospitals.

Population is expected to capture multiple effects, both positive and negative. An expected positive effect on inefficiency is connected with longer waiting times for treatments, both for outpatient preventive care as well as inpatient care. The longer the waiting times, and thus the later the illness is uncovered and treated, the lower the chance of full recovery at

Table 1. Descriptive Statistics

Inputs & outputs	No. obs.	Mean	Median	Minimum	Maximum	Std. Dev.
costs	661	5.072E+08	2.971E+08	4.037E+07	3.506E+09	6.090E+08
non_op_days	661	68771	46666	6759	296140	59798
op_days	661	52111	39272	5124	227318	41510
intense_days	661	14318	7918	723	109552	17355
sum_3_days	661	135200	93795	16062	607026	115660
nursing_days	370	17490	14937	3892	52470	10472
doctor_10_beds	660	1.4728	1.3998	0.4370	3.7606	0.3878
nurse_10_beds	660	5.3495	5.1632	2.6329	13.7757	1.0805
salary	661	15897	15463	11894	24416	2572
Determinants						
teaching	661	0.1241	0	0	1	0.3299
size1	661	0.3147	0	0	1	0.4647
size3	661	0.3570	0	0	1	0.4791
not_profit	661	0.7216	1	0	1	0.4485
population	661	65255	27544	3107	373272	89686
over_65	661	14.173	14.250	8.800	18.300	1.650
competition	661	15.9123	14	5	28	6.7074

a reasonable cost. A positive effect on efficiency, on the other hand, is expected to be represented by the availability of more advanced and modern technologies used for diagnostics and treatments. The process of treatment thus becomes more efficient. The results are expected to depend on which of the two effects (positive or negative) is likely to overweight.

The share of the elderly population (*over_65*) is expressed as a proportion to the total population in the municipality. It is assumed that more people over 65 in municipality increase inefficiency of hospitals since the elderly usually require more demanding and costly treatments such as bypass, recovery after heart-attack, stroke, etc.

Competitive pressures in the hospital market is measured as the number of hospitals in the region (*competition*), consistent with Zuckerman *et al.* (1994). A higher number of hospitals is assumed to increase efficiency. The rationale is based on the assumption that if a public hospital is inefficient, its existence is threatened as it competes for government finances with other public hospitals.

Descriptive statistics of all variables is provided in Table 1. Table A2 shows a correlation matrix both of functional and efficiency variables.

4 Empirical results

Prior to efficiency measurement, the data on output variables was thoroughly analyzed. The correlation between the two sets of output variables initially considered, i.e. patients and patient days, was high (0.9808), so only one set of these outputs (patient days) was decided upon. Examining the different kinds of output (i.e. non-operative, operative, intensive, nursing patient days), a high level of correlation among the first three was discovered varying from 0.88 to 0.93. Including all these variables in the cost function may lead to multicollinearity.

It was thus highly desirable to restructure the data in such a way to keep as much information in the data as possible to account for the output mix but also to avoid multicollinearity. Similar to Janlov (2007), the Principal Components Analysis (further 'PCA')[9] was carried out to reveal internal structure of the data. Table 2 provides the results for patient days in natural units.

Table 2. Principal Components Analysis: patient days

	PC1	PC2	PC3	PC4
Eigenvalue	2.935	0.941	0.077	0.047
Proportion	0.734	0.235	0.019	0.012
Cumulative	0.734	0.969	0.988	1.000
non_op_days	0.566	0.139	0.559	0.589
op_days	0.568	0.048	−0.797	0.199
intense_days	0.570	0.119	0.218	−0.783
nursing_days	0.177	−0.982	0.067	−0.001

The first two components express over 96.92 % of information of the data. We therefore transform the four initial variables and include only two types of care. The first component loadings are assumed to express variance in the first three variables, while the second ones account for the variance in nursing days. When looking at loadings for the first component, their similarity for the three variables concerned (non-operative, operative, intensive care) is striking. Instead of multiplying the original variables by their loadings for each of the two most significant components, we can thus simply transform the data by summing up the non-operative, operative and intensive care days. Hence, only nursing days and sum of the non-operative, operative and intensive care days are included among outputs (*sum_3_days*) besides others.

4.1 Baseline model

We estimated efficiency using the Cobb-Douglas cost function. The baseline model, in which determinants are not included, takes the following form:

$$\begin{aligned}\ln(\text{costs}_{it}) \quad = \quad & \beta_0 + \beta_1 \ln(\text{sum\_3\_days}_{it}) + \beta_2 \ln(\text{nursing\_days}_{it}) + \beta_3 \ln(\text{doctor\_bed}_{it}) + \\ & + \beta_4 \ln(\text{nurse\_bed}_{it}) + \beta_5 \ln(\text{salary}_{it}) + v_{it} + u_{it} \qquad (7)\end{aligned}$$

[9]PCA projects the data on the new coordinate system such that the greatest variance lies on the first coordinate which is expressed by the first component. The second greatest variance is explained by the second component which is however uncorrelated with the first one and so on. Consequently, only the greatest variances are taken into account and thus the original set is transformed into a lower dimensional data not correlated with one another. For explanation of PCA see Jolliffe (2002).

Results of the estimation of (7) are provided in Table 3. Parameter μ was allowed to vary and was significant suggesting that truncated-normally distributed inefficiency term (with non-zero mean) is the case.[10]

Except for nursing days, all of the output variables proved significant and have positive signs. Furthermore, the highest elasticity of the sum of non-operating, operating and intensive days is not surprising since they are assumed to be enormously resource demanding areas of hospital care. The insignificance (even though at the border level) and the negative sign with nursing days was not expected, however. It is believed that there might be a hidden effect of size since big hospitals tend to have nursing wards separated from the hospital itself. They thus have separate accounting and management, and nursing days are not included in the analysis out of methodological reasons. Assuming that big hospital have higher costs and no nursing days integrated into the analysis, being a smaller hospital with some nursing days immediately suggest that nursing days decrease costs, even though insignificantly. The likelihood ratio test on one-sided error term reveals that the difference between using a one-sided error term or excluding it is extremely statistically significant. The inclusion of the inefficiency term into the model is thus appropriate. Moreover, the value of the variance of the inefficiency term is quite large in relation to the variance of the composed error as revealed by the γ parameter. Statistical noise thus accounts only for a small portion of the total error variance.

Table 3. Baseline model

	Coefficient	S.E.	t-ratio	
β_0	6.66479	0.81254	8.202	***
sum_3_days	0.53309	0.04292	12.42	***
nursing_days	−0.00989	0.00788	−1.255	
doctor_bed	0.07115	0.03835	1.855	*
nurse_bed	0.20919	0.07111	2.942	***
salary	0.62413	0.07079	8.817	***
σ^2	0.22084	0.01669	13.23	***
γ	0.93729	0.00852	110.06	***
μ	0.90993	0.07609	11.96	***
Log likelihood function			229.61	
LR one-sided error			612.79	***

Note: ***significant at 1% level, * significant at 10% level.

Table 4 provides summary statistics for the efficiency scores, both for the sample as a whole and in division into groups as described earlier. Mean efficiency for the whole sample is slightly over 0.41 and standard deviation around 0.20 which can also be read from Figure 2. One further notices that there is not a single fully efficient observation. Looking at the standard deviation, it is smaller when hospitals are divided into groups than for the overall sample. It suggests that the division was reasonable revealing a considerable homogeneity of

[10] As a result of prior tests, restriction on parameter η, $\eta = 0$, was imposed, and thus a time–invariant alternative estimated.

hospitals within size groups (big hospitals in particular). It is further apparent that average efficiency decreases as group size increases, being around 0.59 for small hospitals; it falls to around 0.4 for medium hospitals and decreases rapidly for big hospitals. The efficiency scores are however quite low in absolute terms regardless of size of the hospital. Table A3 presents individual efficiency scores and ranking of hospitals.[11]

Table 4. Summary statistics: efficiency scores in the baseline model

	Whole sample	Size 1: $\leq$ 10,000	Size 2: 10,000–20,000	Size 3: $>$ 20,000
mean	0.4105	0.5895	0.3993	0.2428
min	0.1124	0.3730	0.1124	0.1132
max	0.9305	0.9138	0.9305	0.3794
st.dev.	0.1922	0.1452	0.1533	0.0768
no. obs.	99	33	33	33

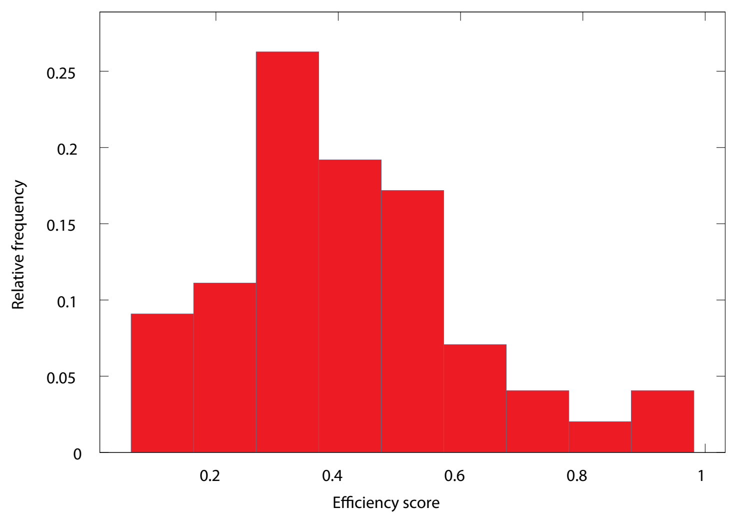

Figure 2. Distribution of average efficiency scores in the baseline model

[11]The interpretation the individual scores is such that when a hospital reaches the efficiency score of 0.8, it employs total costs which are 25 % higher than what it would have been were it frontier efficient. In other words, there is a scope for efficiency improvement reaching 20 percentage points.

4.2 Model with determinants

In this section, we present estimation results, when determinants are included in the model. Battese and Coelli (1995) method allows us to estimate efficiency and its determinants in one step which avoids a problem of serial correlation present in a two-step estimation. The cost function is the same as in (7), but the inefficiency term takes the following form:

$$\begin{aligned} u_{it} &= \delta_0 + \delta_1 \text{ teaching} + \delta_2 \text{ size1} + \delta_3 \text{ size3} + \delta_4 \text{ not\_profit} + \delta_5 \text{ population} + \\ &\quad + \delta_6 \text{ over\_65} + \delta_7 \text{ competition} + \omega_{it} \end{aligned} \tag{8}$$

Results are provided in Table 5. All variables of the cost function are significant. As opposed to the regression without determinants, not only did the variable for nursing days prove to significantly influence costs even at 1 % level but the coefficient is positive as well. It is believed that a hidden effect in the output variable 'nursing days' in the results of the baseline model is uncovered when determinants are included in the model. Of all the output variables, the highest elasticity was for the sum of non-operative, operative and intensive care days, which is consistent with Table 3. The sum of coefficients for output variables is bigger than one. Since axes are reversed in the input orientation (input, output), decreasing returns to scale are present.

Table 5. Model with determinants

	Coefficient	S.E.	t-ratio	
β_0	6.33286	1.02738	6.164	***
sum_3_days	0.84386	0.03293	25.63	***
nursing_days	0.01676	0.00235	7.132	***
doctor_bed	0.37563	0.05380	6.982	***
nurse_bed	0.68356	0.06603	10.35	***
salary	0.45600	0.09724	4.689	***
δ_0	0.03765	0.08395	0.448	
teaching	0.42822	0.05008	8.551	***
size1	−0.23717	0.06650	−3.567	***
size3	0.08460	0.04144	2.042	**
not-profit	0.14022	0.04417	3.174	***
population	−4.89E-07	0.00000	−3.062	***
over_65	0.00566	0.00424	1.336	†
competition	−0.00413	0.00268	−1.540	†
σ^2	0.06313	0.00393	16.06	***
γ	0.01387	0.00627	2.214	**
Log likelihood function			−24.19	
LR one-sided error			105.16	***

Note: *** significance at 1% level, ** significance at 5% level, † one-tail significance at 10% level.

The likelihood ratio test on one-sided error term, i.e. the test on the presence of the inefficiency term, is significant suggesting that the inefficiency term is highly appropriate in the analysis. Parameter γ is also significant but much smaller than in the baseline analysis. It means that the variance of the inefficiency term takes up a much smaller part of the total variance than before. In other words, compared to the previous regression, more of the total variance of the error term is now captured by the variance of the white noise rather than inefficiency since a certain portion of inefficiency was explained by determinants and thus is smaller than before.

All determinants of inefficiency proved significant. Teaching status has a positive effect on inefficiency as expected, moreover, its coefficient is the largest of all the determinants. The result thus confirms that teaching hospitals are very special in their nature. They incur specific costs connected with teaching material, facility or personnel. Additionally, size dummies indicate that being a very small hospital decreases inefficiency while being very big has a positive effect of inefficiency, even though by quite a small amount. The results suggest that there are decreasing returns to scale present in the production technology of hospitals and thus being of a certain size should explain some portion of inefficiency.

Hospitals with not-for-profit status tend to be more inefficient than for-profit hospitals. The result is consistent with the initial hypothesis keeping in mind that the purpose of transformation into joint-stock companies was to curb extensive costs and inefficiency. For-profit hospitals seem to manage resources in a more efficient way.

If a hospital is situated in a bigger municipality in terms of its population, it seems to be more efficient. Population may influence inefficiency of hospitals by various channels; the occupancy rate may be higher in bigger cities and thus hospitals demonstrate more patient days; at the same time, the quality effect which decreases because of higher occupancy rate (medical staff does not have so much time for each patient, patients do not have separate rooms) increases through the availability of better medical equipment and more advanced, effective and less costly means of treatment.

The higher the share of the elderly, the higher the inefficiency of hospitals as expected. The coefficient proved significant at 10 % at one-tail distribution. The hypothesis of the negative effect on inefficiency is significantly rejected. It is consistent with the findings of Frohloff (2007) who concluded that a large share of the elderly increases inefficiency of hospitals considerably.

The sign of the coefficient for the number of hospitals in the region is negative which is consistent with the initial assumption that competition exerts pressures to decrease inefficiency. The coefficient proved significant at 10 % one-tail, however. We thus reject the null hypothesis of a positive effect of this variable. The same result concerning the sign of the coefficient was reached by Zuckerman *et al.* (1994) who measured efficiency of hospitals in the U.S.A., however their coefficient proved insignificant.[12]

Cross-sectional efficiency scores were obtained for individual years for each hospital. However, Spearman's Rank Coefficient was calculated to obtain intertemporal correlation. The results revealed the rankings of the efficiency scores to be stable over time, with the correlation

[12]An alternative measure of competition was tested such that the number of hospitals in the region was weighted by the size of the population of respective regions. It was expected that in bigger regions competition among hospitals is less harmful. Weighting by population was assumed to account for this problem. Nevertheless the weighted competition variable proved insignificant.

coefficients varying from 0.94 to 0.99 for the neighboring years. Therefore, there is no loss of information when results for each hospital are averaged over time. Averaged efficiency scores are provided in Table A3. Table 6 summarizes statistics for the whole sample as well as for size groups. The results are further supported by the distribution of average efficiency scores in Figure 3. Interestingly, having accounted for size in the regression, differences among groups with respect to average efficiency pertain, even though decrease considerably compared to the specification without determinants. It is also worth pointing out that standard deviation is again smaller when the sample is divided according to size groups. However, as opposed to the regression without determinants where it was the lowest, standard deviation is the largest for big hospitals. It is thus expected that there might be omitted variables connected only with some bigger hospitals which influence their efficiency. This serves as motivation for further research.

Table 6. Summary statistics: efficiency scores in the model with determinants

	Whole sample	Size 1: $\leq$ 10,000	Size 2: 10,000–20,000	Size 3: $>$ 20,000
mean	0.8634	0.9926	0.8753	0.7223
min	0.5007	0.9820	0.8086	0.5007
max	0.9972	0.9972	0.9818	0.8982
st.dev.	0.1328	0.0038	0.0379	0.1213
no. obs.	99	33	33	33

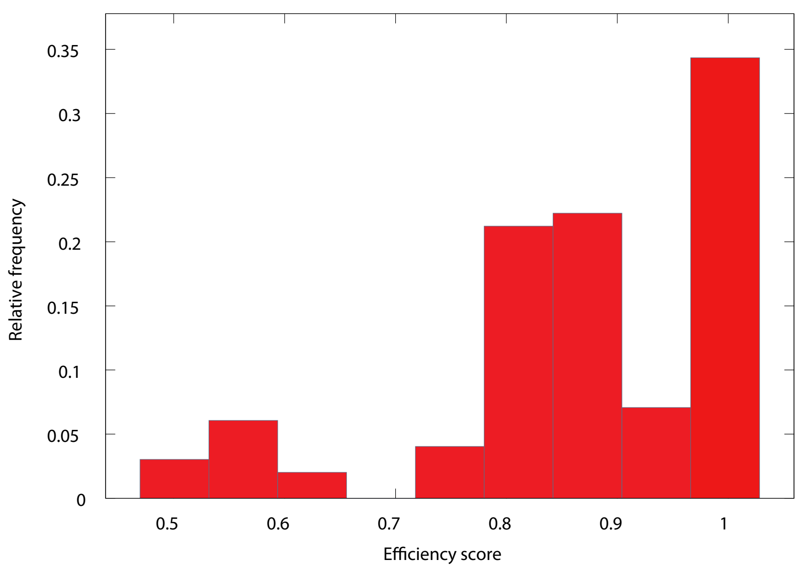

Figure 3. Distribution of average efficiency scores with determinants

4.3 Discussion

Individual efficiency scores increased with the incorporation of determinants, from 0.41 to 0.86 in the mean for the whole sample. It suggests that using determinants is important since otherwise low efficiency scores might be wrongly regarded as inefficiency while instead being caused by various individual-specific characteristics beyond the control of hospitals. The total standard deviation of the efficiency scores also decreased remarkably. Since it is impossible to compare efficiency scores, efficiency rankings of the two different sets of results were analyzed instead. The obtained Spearman's Rank Correlation Coefficient for the whole sample is 0.8091. Nevertheless, on the disaggregated level, the correlation is either insignificant or significant with a low coefficient (big hospitals). It implies that individual-specific determinants cause some asymmetric shifts in efficiency ranks depending on the characteristics of each hospital. However, rankings differ mainly within groups than across groups.[13]

Table 7. Hospitals in top and bottom deciles

Baseline model		Model with determinants	
Top decile	Bottom decile	Top decile	Bottom decile
Milosrd. bratří, Brno	Na Homolce, Praha	Rumburk	FN Hradec Králové
Jeseník	FN Brno	Karviná	FN Olomouc
Hranice	FN Olomouc	Brandýs n. L.	FN Plzeň
Opočno	FN Hradec Králové	Kutná Hora	FN Král. Vinohrady, Praha
Mladá Boleslav	FN Sv. Anna, Brno	VN Brno	FN Thomayerova, Praha
Trutnov	FN Motol, Praha	Sedlčany	FN Na Bulovce, Praha
Dvůr Králové n. L.	FN Ostrava	Roudnice n. L.	VFN Praha
Sedlčany	FN Plzeň	Rychnov n. K.	FN Ostrava
Sušice	VFN Praha	Hranice	FN Motol, Praha
Kadaň	Ústí n. Labem	Kadaň	FN Sv. Anna, Brno

Note: The first hospital in the top (bottom) decile is the most (least) efficient in the sample. FN = teaching hospital, VN = military hospital.

Table 7 identifies the most and least efficient hospitals under the model with and without determinants. A closer scrutiny reveals that hospitals with the highest efficiency scores belong to the group of small hospitals (with two exception from medium hospitals). On the other hand, the group of the least efficient hospitals is formed primarily by teaching hospitals[14] which belong to the group of big hospitals, and is quite stable across methods. The exceptions in the bottom decile without determinants are hospital in Ústí nad Labem which is a very large hospital, and hospital Na Homolce which approaches patients on very individual basis. These are, however, not classified as least efficient when determinants are included. It thus suggests that with the inclusion of determinants, these hospitals improved their relative position in the sample. Bottom decile in the model with determinants is taken up by teaching hospitals exclusively.

[13] Table A4 provides overview of results, as well as Spearman's correlations.

[14] There are 11 teaching hospitals in the Czech Republic, Hradec Králové, U sv. Anny - Brno, Brno, Olomouc, Ostrava, Plzeň, VFN Praha, Thomayerova, Motol, Na Bulovce, Královské Vinohrady

Consequently, shifts in ranks for average efficiency scores between model with and without determinants were analyzed for the entire sample. Average shift was by 13.5 ranks for all 99 observations. On the disaggregated level, the biggest changes are observed for medium hospitals, by 16 ranks on average. Table 8 lists the most positively and negatively effected hospital and their group affiliations as well as the number of ranks by which the position changed. Hospitals Na Homolce, ÚVN Praha and VN Brno experienced major improvements. These hospitals are very special in their nature and thus had originally been disadvantaged when determinants were not accounted for. Nevertheless, one notices that major shifts towards higher ranks are not very much group specific. On the other hand, major deteriorations took place primarily in groups of medium and big hospitals. Moreover, when looking at the ownerhsip structure of hospitals in Table 8, it reveals that enormous improvements in ranks took place for not-for-profit hospitals (top three improvements), while major deteriorations took place among for profit hospitals (top two deteriorations).

Table 8. Major improvements and deteriorations of ranks

Improvement			Deterioration		
size	ID	change	size	ID	change
2	Na Homolce, Praha	52	2	Valašské Meziříčí	−51
2	VN Praha	43	2	Svitavy	−35
1	VN Brno	40	2	Slaný	−34
1	Karvinská hornická	38	2	Trutnov	−33
1	Hodonín	28	2	Milosrdných bratří, Brno	−33
2	Kolín	27	3	Nové Město na Moravě	−33
3	Městská nemocnice Ostrava	26	3	Teplice	−25
3	Ústí n. Labem	24	3	Kyjov	−23
2	Benešov	24	1	Sušice	−23

Note: Plus denotes shifts towards higher ranks and visa versa. Size 1=small, 2=medium, 3=big hospitals.

Average efficiency scores from the model with determinants for individual hospitals were further averaged for each region. Table 9 shows average efficiency scores and ranks for regions. Karlovarský region ended up as the most efficient, however, the results should be interpreted with caution since only one hospital from that region was included in the analysis. Furthermore, there are mostly big hospitals, i.e. the most inefficient group, in the Vysočina region. The Capital of Prague has the lowest average efficiency score of all the regions reaching only 0.6973 since majority of teaching hospitals, which belong to the least efficient ones in the analysis, are situated in Prague. Indeed, comparison with Table 7 reveals that 5 from the 10 least efficient hospitals are situated in Prague. On the other hand, three from the most efficient hospitals belong to the Ústí region (Rumburk, Roudnice n. L., Kadaň) and two to the Central Bohemian region (Brandýs n. L., Kutná Hora). Comparison of individual and aggregated results however suggests that, except for Prague, efficiency scores for hospitals within regions are rather dispersed.

Table 9. Average efficiency of hospitals in regions

Region	Obs. IDs	Efficiency	Rank
Karlovy Vary Region	15	0.9938	1
Ústí Region	67–74	0.9118	4
Central Bohemian Region	75–86	0.9350	2
Liberec Region	16–22	0.9168	3
South Bohemian Region	1–7	0.8952	6
Plzeň Region	61–66	0.8999	5
Hradec Králové Region	8–14	0.8832	7
Moravian–Silesian Region	44–55	0.8569	9
Olomouc Region	34–40	0.8629	8
South Moravian Region	23–33	0.8550	10
Zlín Region	95–99	0.8264	11
Pardubice Region	41–43	0.8199	12
Vysočina Region	56–60	0.7611	13
Prague	87–94	0.6973	14

In any case, the results suggest that Czech hospitals are not on average overly relatively inefficient when determinants of inefficiency are identified and taken care of. Table 10 provides an overview of the number of hospitals classified in intervals corresponding to efficiency scores. Having accounted for determinants, a high level of inefficiency is rather group-specific. In particular, efficiency scores for teaching hospitals are much lower compared even to other big hospitals, i.e. the score for the most efficient teaching hospital reaches 0.6086 with determinants but immediately following another big hospital with score of 0.7377. In further research, we will thus concentrate on outputs specific for big and teaching hospitals.

Table 10. Number of hospitals in intervals: model with determinants

	Whole sample	Small	Medium	Big	Teaching
<0.6	10	0	0	10	10
0.6–0.7	1	0	0	1	1
0.7–0.8	10	0	0	10	0
0.8–0.9	37	0	25	12	0
0.9–1	41	33	8	0	0
Total	99	33	33	33	11

5 Conclusion

This paper examined cost efficiency of 99 general hospitals in the Czech Republic in the period 2001–2008. Stochastic frontier analysis was employed. Having added determinants of inefficiency into the SFA regression, an additional model was developed. Efficiency of Czech hospitals was evaluated and compared under both models. At the same time, effects of various environmental factors on inefficiency were discussed.

Concerning determinants, teaching status increases inefficiency since additional costs connected with teaching material, staff, etc. are incurred. Being a very small hospital decreases inefficiency, while being very big increases it. Not-for-profit status was found to increase inefficiency. These findings support reasons for the ongoing privatization process of Czech hospitals. Size of the population in the municipality where the hospital is situated was found to increase efficiency. The results thus show that the effect of more advanced, complex and efficient care in bigger cities overweight the effect of longer waiting times (and costly care afterwards). The share of the elderly in the population tends to increase inefficiency of hospitals. The number of hospitals in the region was found to decrease inefficiency, consistent with the hypothesis.

Having accounted for determinants, efficiency scores of all hospitals remarkably increased. Furthermore, with the inclusion of determinants, rankings within the group of all hospitals changed, suggesting that determinants exerted asymmetric effects on hospitals, depending on the characteristic features of each of the analyzed hospitals. The most profound shifts took place among medium hospitals which treat 10,000–20,000 patients a year.

The results of the model with determinants reveal that Czech hospitals are not overly relatively inefficient as a whole, as differences of scores are not as large. Nevertheless, it has been uncovered that the persistence of inefficiency is rather group specific. Put differently, even having accounted for size and teaching status, teaching and very big hospitals in general preserve some level of inefficiency. Furthermore, the scores for big hospitals are rather dispersed. The results suggest that when additional determinants of inefficiency specific for teaching hospitals in particular are accounted for, their efficiency might increase. In further research, we will concentrate on the identification of these variables.

Besides, the paper has a number of other implications. The panel has been restricted to 8 years of observations in an unbalanced form. Extension to a balanced panel with more observations for each hospital would enable a more extensive intertemporal comparison of the results.

The system of Diagnostic-Related Groups, common abroad as a case mix adjustment mechanism in efficiency analyses, is currently being developed in the Czech Republic. Once the system functions fully, variations in output-mix would be accounted for more precisely. The motivation is thus to replicate the results once this information is available.

Effects of alternative determinants and variables for input prices should be tested in further research. These include accounting directly for wages of medical staff instead of using average salary in the district as a proxy for input prices. The data was however, not available when this analysis was carried out. The competition variable could take into account distances to other hospitals instead of accounting for the number of hospitals in the region as such.

Moreover, the effect of the process of transformation of hospitals, rather than only ownership status, should be tested.

The results of this analysis should not serve as a background for immediate policy responses. It rather points out to special circumstances and provides motivation for further research. At the same time, it is fully acknowledged that economic analysis of Czech hospitals is not telling the whole story. It should be supplemented by surveys of satisfaction with the quality of care, etc. in order for the analysis to provide an overall picture.

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Appendix

Table A1. Overview of hospitals

ID	Name	ID	Name
1	Nemocnice České Budějovice, a.s.	51	Nemocnice s poliklinikou Nový Jičín, p.o.
2	Nemocnice Český Krumlov, a.s.	52	Bílovecká nemocnice, a.s.
3	Nemocnice Jindřichův Hradec, a.s.	53	Slezská nemocnice v Opavě,p.o.
4	Nemocnice Písek,a.s.	54	FNsP Ostrava
5	Nemocnice Prachatice, a.s.	55	Městská nemocnice Ostrava, p.o.
6	Nemocnice Strakonice, a.s.	56	Nemocnice Havlíčkův Brod, p.o.
7	Nemocnice Tábor, a.s.	57	Nemocnice Jihlava, p.o.
8	Fakultní nemocnice Hradec Králové	58	Nemocnice Pelhřimov, p.o.
9	Oblastní nemocnice Jičín, a.s.	59	Nemocnice Třebíč, p.o.
10	Oblastní nemocnice Náchod, a.s.	60	Nemocnice v N. město na Moravě, p.o.
11	Oblastní nemocnice Rychnov n. Kněžnou, a.s.	61	Domažlická nemocnice, a.s. Domažlice
12	Oblastní Nemocice Náchod, a.s. Opočno	62	Klatovská nemocnice, a.s., Klatovy
13	Městká nemocnice, a.s. Dvůr Králové n. L.	63	Nemocnice Sušice, o.p.s.
14	Oblastní nemocnice Trutnov, a.s.	64	Fakultní nemocnice Plzeň
15	Nemocnice Mariánské Lázně, s.r.o.	65	Stodská nemocnice, a.s., Stod
16	NsP Česká Lípa, a.s.	66	Rokycanská nemocnice, a.s. Rokycany
17	Nemocnice Jablonec n. Nisou, p.o.	67	Krajská zdravotní,a.s. - Nem. Děčín
18	Krajská nemocnice Liberec, a.s.	68	Lužická nemocnice a poliklinika, a.s. Rumburk
19	Nemocnice Frýdlant, s.r.o.	69	Krajská zdravotní, a.s. - Nem. Chomutov, o.z.
20	Masarykova městská nemocnice Jilemnice	70	Nemocnice Kadaň, s.r.o.
21	Panochova nemocnice Turnov, s.r.o.	71	Podřipská NsP Roudnice n. Labem, s.r.o.
22	NsP Semily, p.o.	72	Krajská zdravotní, a.s. - Nemocnice Most, o.z
23	Fakultní nemocnice U sv. Anny, Brno, p.o.	73	Krajská zdravotní, a.s. - Nemocnice Teplice, o.z.
24	Nemocnice Milosrdných Bratří,p.o. Brno	74	Kr. zdrav., a.s. - Masaryk. nem. Ústí n. Lab., o.z.
25	Fakultní nemocnice Brno, Brno	75	Nemocnice Rudolfa a Stefanie Benešov, a.s.
26	Vojenská nemocnice Brno, p.o.	76	NH Hospitals, s.r.o. Nemocnice Hořovice
27	Nemocnice Ivančice, p.o. Ivančice	77	Oblastní nemocnice Kladno, a.s.
28	Nemocnice Břeclav,p.o. Břeclav	78	Nemocnice Slaný, p.o.
29	Městská nemocnice Hustopeče, p.o	79	ON Kolín, a.s.
30	Nemocnice TGM Hodonín, p.o. Hodonín	80	Nemocnice Kutná Hora, s.r.o
31	Nemocnice Kyjov, p.o. Kyjov	81	Mělnická zdravotní, a.s.,NsP Mělník
32	Nemocnice Vyškov, p.o.	82	ON Mladá Boleslav, a.s.
33	Nemocnice Znojmo, p.o.	83	PP Hospitals, s.r.o. Nemocnice Brandýs nad Lab.
34	Jesenická nemocnice, s.r.o., Jeseník	84	Oblastní nemocnice Příbram,a.s.
35	FN Olomouc	85	MEDITERRA - Sedlčany, s. r. o.
36	Vojenská nemocnice, Olomouc, Klášter.Hradisko	86	PRIVAMED Healthia, s.r.o. NsP Rakovnik
37	Středomor. nemocniční,a.s. - Nem. Šternberk	87	Nemocnice Na Františku s poliklinikou
38	Středomor. nemocniční, a.s. - Nem. Prostějov	88	Všeobecná fakultní nemocnice v Praze
39	Středomor. nemocniční, a.s. Přerov	89	Fakultní Thomayerova nemocnice s poliklinikou
40	Nemocnice Hranice, a.s. Hranice	90	Nemocnice na Homolce
41	Chrudimská nemocnice, a.s. Chrudim	91	Fakultní nemocnice Motol
42	Pardubická krajská nemocnice, a.s. Pardubice	92	Fakultní nemocnice Na Bulovce
43	Svitavská nemocnice, a.s. Svitavy	93	Ústřední vojenská nemocnice, Praha 6
44	Nemocnice Krnov, p.o	94	Fakultní nemocnice Královské Vinohrady
45	Nemocnice ve Frýdku-Mistku, p.o	95	Kroměříźská nemocnice, a.s. Kroměříž
46	Nemocnice Třinec, p.o	96	Uherskohradišťská nemocnice,a.s.
47	Nemocnice s poliklinikou, Karviná - Ráj, p.o.	97	Vsetínská nemocnice, a.s., Vsetín
48	Nemocnice s poliklinikou Havířov, p.o.	98	Nemocnice Valašské Meziříčí, a.s.
49	Bohumínská městská nemocnice, a.s. Bohumín	99	Krajská nemocnice T. Bati, a.s. Zlín
50	Karvinská hornická nemocnice, a.s.		

Note: Name valid in the year 2008

Table A2. Correlation matrix

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
1	0.203	0.3359	0.3641	0.4184	0.7922	−0.5427	0.7472	0.3064	0.6564	0.3024	0.2074	sum_3_days (1)
	1	−0.0405	−0.1028	−0.0328	0.238	−0.2517	0.2062	0.0769	0.2143	−0.1376	−0.1626	nursing_days (2)
		1	0.6586	0.5261	0.3193	−0.2311	0.1731	0.0662	0.3019	0.2623	0.1639	doctor_bed (3)
			1	0.4157	0.3065	−0.2846	0.2296	0.0638	0.3611	0.2697	0.158	nurse_bed(4)
				1	0.4818	−0.1338	0.2961	−0.0269	0.4478	0.4357	0.4375	salary (5)
					1	−0.255	0.505	0.2337	0.6352	0.3526	0.2562	teaching (6)
						1	−0.5049	−0.3278	−0.2974	−0.0655	−0.0665	size1 (7)
							1	0.2937	0.4456	0.0891	0.1181	size3 (8)
								1	0.2735	−0.0628	0.1843	not_profit (9)
									1	0.3355	0.3317	population (10)
										1	0.0713	over_65 (11)
											1	competition (12)

Table A4. Summary statistics and correlations across methods: average scores

	obs.	mean	min	max	st.dev.	Rank correlation Baseline	With det.
Whole Sample							
Baseline	99	0.4105	0.1124	0.9305	0.1922	1	
With determinants	99	0.8634	0.5007	0.9972	0.1328	0.8091***	1
Size 1: $\leq$ 10,000							
Baseline	33	0.5895	0.3730	0.9138	0.1452	1	
With determinants	33	0.9926	0.9820	0.9972	0.0038	0.1426	1
Size 2: 10,000–20,000							
Baseline	33	0.3993	0.1124	0.9305	0.1533	1	
With determinants	33	0.8753	0.8086	0.9818	0.0379	0.1527	1
Size 3: $>$ 20,000							
Baseline	33	0.2428	0.1132	0.3794	0.0768	1	
With determinants	33	0.7223	0.5007	0.8982	0.1213	0.5006***	1

Note: *** significant at 1% level.

Table A3. Efficiency scores and ranks: baseline model and model with determinants

Size	ID	Baseline eff.	Baseline rank	With det. eff.	With det. rank	Size	ID	Baseline eff.	Baseline rank	With determinants eff.	With determinants rank
3	1	0.2110	87	0.8401	65	2	51	0.4167	41	0.8575	58
1	2	0.4222	39	0.9893	28	1	52	0.5533	22	0.9931	17
2	3	0.2907	73	0.8628	53	3	53	0.2934	71	0.7913	81
2	4	0.4277	38	0.8580	57	3	54	0.1425	93	0.5833	92
1	5	0.5577	21	0.9903	27	3	55	0.3023	69	0.8982	43
2	6	0.3804	48	0.8599	55	3	56	0.2833	76	0.7377	88
2	7	0.3237	60	0.8663	50	3	57	0.2598	81	0.7529	86
3	8	0.1139	96	0.5007	99	2	58	0.2874	74	0.8086	75
2	9	0.4336	37	0.8950	44	3	59	0.3046	67	0.7596	85
2	10	0.3411	57	0.8861	45	3	60	0.3636	54	0.7469	87
1	11	0.4824	30	0.9954	8	1	61	0.5195	24	0.9921	21
1	12	0.8912	4	0.9949	14	2	62	0.4569	35	0.9143	40
1	13	0.7534	7	0.9953	11	1	63	0.7118	9	0.9839	32
2	14	0.8391	6	0.9151	39	3	64	0.1436	92	0.5247	97
1	15	0.4743	34	0.9938	16	1	65	0.6153	13	0.9922	19
3	16	0.2629	80	0.8173	72	1	66	0.4798	31	0.9921	20
2	17	0.2660	79	0.8283	68	2	67	0.4987	28	0.9250	37
3	18	0.2167	86	0.8237	70	1	68	0.5665	20	0.9972	1
1	19	0.5816	15	0.9951	13	2	69	0.4128	43	0.9091	41
1	20	0.5422	23	0.9840	31	1	70	0.7087	10	0.9953	10
1	21	0.5006	27	0.9875	30	1	71	0.5708	19	0.9956	7
1	22	0.6239	12	0.9820	33	3	72	0.3144	65	0.8273	69
3	23	0.1146	95	0.5984	90	3	73	0.3794	49	0.8099	74
2	24	0.9305	1	0.9818	34	3	74	0.1729	90	0.8350	66
3	25	0.1132	98	0.6086	89	2	75	0.3223	62	0.9209	38
1	26	0.4104	45	0.9964	5	1	76	0.5028	26	0.9928	18
1	27	0.4760	33	0.9911	25	3	77	0.2550	82	0.8143	73
3	28	0.3274	59	0.8029	77	2	78	0.5725	18	0.8632	52
1	29	0.6517	11	0.9921	22	2	79	0.3199	63	0.9263	36
1	30	0.3730	51	0.9921	23	1	80	0.5728	17	0.9964	4
3	31	0.3228	61	0.7883	84	2	81	0.3832	46	0.8996	42
2	32	0.3041	68	0.8620	54	3	82	0.3177	64	0.8693	49
3	33	0.3137	66	0.7910	82	1	83	0.8644	5	0.9964	3
1	34	0.9138	2	0.9952	12	2	84	0.3469	56	0.9502	35
3	35	0.1135	97	0.5022	98	1	85	0.7470	8	0.9962	6
1	36	0.5908	14	0.9893	29	1	86	0.4768	32	0.9949	15
2	37	0.4143	42	0.8405	64	1	87	0.4909	29	0.9919	24
2	38	0.3819	47	0.8516	59	3	88	0.1611	91	0.5747	93
2	39	0.4110	44	0.8659	51	3	89	0.2874	75	0.5531	95
1	40	0.9011	3	0.9953	9	2	90	0.1124	99	0.8744	47
2	41	0.2922	72	0.8476	62	3	91	0.1410	94	0.5929	91
3	42	0.2462	84	0.7893	83	3	92	0.2357	85	0.5551	94
2	43	0.4358	36	0.8228	71	2	93	0.1877	89	0.8853	46
2	44	0.3794	50	0.8510	60	3	94	0.1980	88	0.5513	96
3	45	0.2666	78	0.8036	76	2	95	0.3384	58	0.8581	56
2	46	0.3553	55	0.8499	61	3	96	0.2805	77	0.7942	80
3	47	0.3014	70	0.7963	79	2	97	0.3723	52	0.8469	63
2	48	0.3692	53	0.8707	48	2	98	0.5730	16	0.8303	67
1	49	0.5080	25	0.9909	26	3	99	0.2515	83	0.8028	78
1	50	0.4195	40	0.9968	2						

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Appendix C

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There is a CD enclosed to this thesis which contains a LaTeX source file and a pdf version of this thesis.