Institute of Economic Studies, Faculty of Social Sciences
Charles University in Prague

Efficiency of Hospitals in the Czech Republic

Jana Procházková
Lenka Šťastná

IES Working Paper: 2/2011

Institute of Economic Studies,
Faculty of Social Sciences,
Charles University in Prague

[UK FSV – IES]

Opletalova 26
CZ-110 00, Prague
E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Institut ekonomických studií
Fakulta sociálních věd
Univerzita Karlova v Praze

Opletalova 26
110 00 Praha 1

E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Bibliographic information:
Procházková, J., Šťastná, L. (2011). “Efficiency of Hospitals in the Czech Republic” IES Working Paper 2/2011. IES FSV. Charles University.

Efficiency of Hospitals in the Czech Republic

Jana Procházková*
Lenka Šťastná#

* IES, Charles University Prague
E-mail: prochazkova.jana@hotmail.com

IES, Charles University Prague

January 2011

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

Acknowledgements:
We are thankful to Martin Gregor and the ETPM seminar participants at the Institute of Economic Studies, Charles University in Prague, for their helpful comments and suggestions. Financial support by GACR 402/08/0501 and MSMT 0021620841 grants are gratefully acknowledged.

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

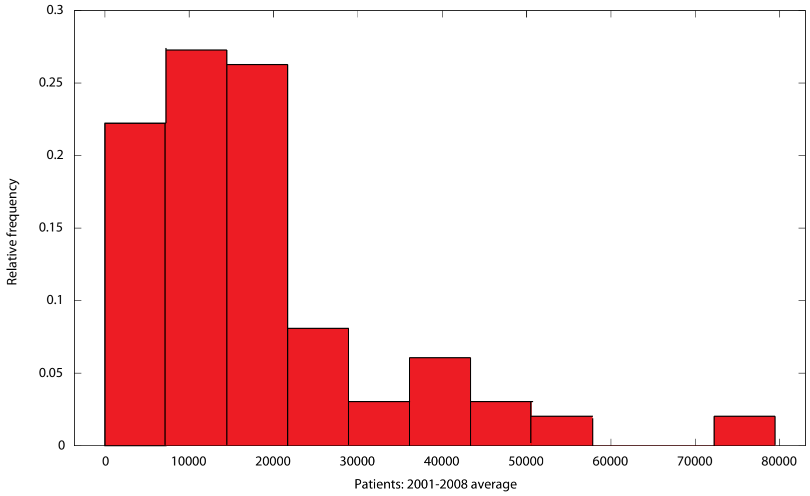

Figure 1. Size distribution of hospitals

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:

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

---

[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

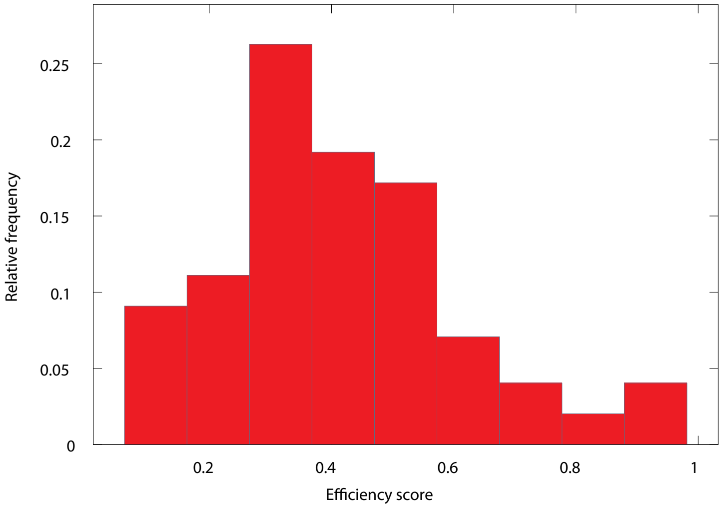

Figure 2. Distribution of average efficiency scores in the baseline model

---

[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

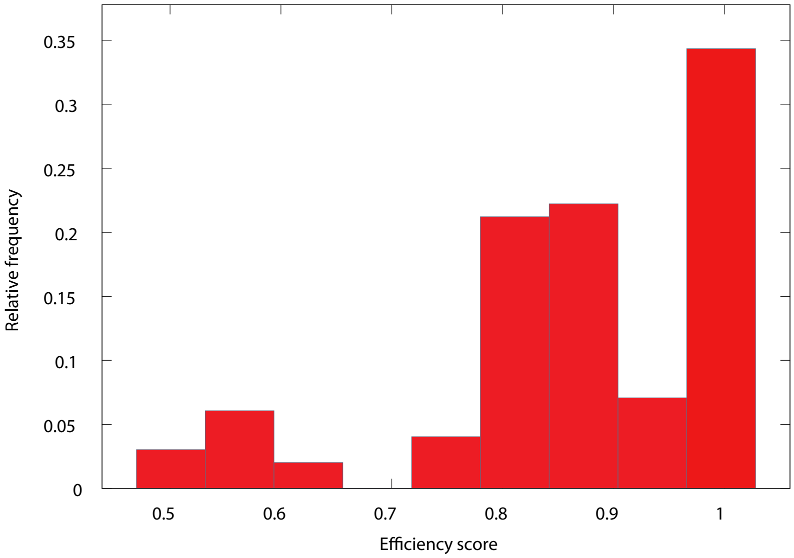

Figure 3. Distribution of average efficiency scores with determinants

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.

References

AIGNER, D., C. A. K. LOVELL, & P. SCHMIDT (1977): "Formulation and Estimation of Stochastic Frontier Production Function Models." *Journal of Econometrics* **6(1)**: pp. 21–37.

BATTESE, G. & T. J. COELLI (1992): "Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India." *The Journal of Productivity Analysis* **3**: pp. 153–169.

BATTESE, G. E. & T. J. COELLI (1988): "Prediction of Firm-Level Technical Efficiencies with a Generalized Frontier Production Function and Panel Data." *Journal of Econometrics* **38(3)**: pp. 387–399.

BATTESE, G. E. & T. J. COELLI (1995): "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data." *Empirical Economics* **20(2)**: pp. 325–32.

BATTESE, G. E. & G. S. CORRA (1977): "Estimation of a Production Frontier Model: with Application to the Pastoral Zone of Eastern Australia." *Australian Journal of Agricultural Economics* **21:3**: pp. 169–179.

CHARNES, A., W. W. COOPER, & E. RHODES (1978): "Measuring Efficiency of Decision Making Units." *European Journal of Operational Research* **2**: pp. 429–444.

CHIRIKOS, T. N. & A. M. SEAR (2000): "Measuring Hospital Efficiency: A Comparison of Two Approaches." *Health Service Research* **34:6**: pp. 1389–1408.

COELLI, T. J. (1996a): *A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program, Working Paper 08/96.* Centre for Efficiency and Productivity Analysis (CEPA), CEPA Working Papers Department of Econometrics University of New England Armidale, NSW 2351s, Australia.

COELLI, T. J. (1996b): *Frontier Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation Working Paper 07/96.* Centre for Efficiency and Productivity Analysis (CEPA), CEPA Working Papers Department of Econometrics University of New England Armidale, NSW 2351s, Australia.

COELLI, T. J., P. D. RAO, C. J. O'DONNELL, & G. E. BATTESE (2005): *An Introduction to Efficiency and Productivity Analysis.* Springer, 2nd Edition.

COTTRELL, A. & R. LUCCHETTI (2007): *Gretl User's Guide.*

DLOUHÝ, M., J. JABLONSKÝ, & I. NOVOSÁDOVÁ (2007): "Využití analýzy obalu dat pro hodnocení efektivnosti českých nemocnic." *Politická ekonomie* **1**: pp. 60–71.

FARRELL, M. J. (1957): "The Measurement of Productive Efficiency." *Journal of the Royal Statistical Society. Series A (General)* **120:3**: pp. 253–290.

FARSI, M. & M. FILIPPINI (2004): "An Analysis of Efficiency and Productivity in Swiss Hospitals." Quaderno N. 05-01.

FOLLAND, S. T. & R. A. HOFLER (2001): "How Reliable are Hospital Efficiency Estimates? Exploiting the Dual to Homothetic Production." *Health Economics* **10(8)**: pp. 683–698.

FROHLOFF, A. (2007): "Cost and Technical Efficiency of German Hospitals: A Stochastic Frontier Analysis." .

GREENE, W. (2003): "Distinguishing between Heterogeneity and Inefficiency: Stochastic Frontier Analysis of the World Healh Organization's Panel Data on National Health Care Systems." .

HOFMARCHER, M. M., I. PETERSON, & M. RIEDEL (2002): "Measuring Hospital Efficiency in Austria - A DEA Approach." *Health Care Management Science* **5**: pp. 7–14.

HOLLINGSWORTH, B. (2008): "The Measurement of Efficiency and Productivity of Health Care Delivery." *Health Economics* **17(10)**: pp. 1107–1128.

INSTITUTE OF HEALTH INFORMATION AND STATISTICS OF THE CZECH REPUBLIC (2001-2008): "Data Presentation System." Database.

INSTITUTE OF HEALTH INFORMATION AND STATISTICS OF THE CZECH REPUBLIC, REGIONAL OFFICES (2001-2008): "Zdravotnictví (kraje + ČR)." *Technical report*, ÚZIS ČR.

INSTITUTE OF HEALTH INFORMATION AND STATISTICS OF THE CZECH REPUBLIC, REGIONAL OFFICES (2004-2005): "Provozně-ekonomické informace lůžkových zařízení v ... kraji." *Technical report*, ÚZIS ČR.

JACOBS, R. (2001): "Alternative Methods to Examine Hospital Efficiency: Data Envelopment Analysis and Stochastic Frontier Analysis." *Health Care Management Science* **4**: pp. 103–116.

JANLOV, N. (2007): "Swedish Health Care Performance - Quantity versus Quality." .

JOLLIFFE, I. T. (2002): *Principal Component Analysis.* Springer USA.

Jondrow, J., C. A. Knox Lovell, I. S. Materov, & P. Schmidt (1982): "On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model." *Journal of Econometrics* **19(2-3)**: pp. 233–238.

Kontodimopoulos, N., P. Nanos, & D. Niakas (2006): "Balancing Efficiency of Health Services and Equity of Access in Remote Areas in Greece." *Health Policy* **76(1)**: pp. 49–57.

Magnussen, J. (1996): "Efficiency Measurement and the Operationalization of Hospital Production." *Health Service Research* **31:1**: pp. 21–37.

Meeusen, W. & J. van den Broeck (1977): "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error." *International Economic Review* **18(2)**: pp. 435–44.

Nayar, P. & Y. A. Ozcan (2008): "Data Envelopment Analysis Comparison of Hospital Efficiency and Quality." *J. Med. Syst.* **32(3)**: pp. 193–199.

Nunamaker, T. R. (1983): "Measuring Routine Nursing Service Efficiency: A Comparison of Cost per Patient Day and Data Envelopment Analysis Models." *Health Service Research* **18**: pp. 183–205.

Prior, D. (1996): "Technical Efficiency and Scope Economics in Hospitals." *Applied Economics* **28**: pp. 1295–1301.

R Development Core Team (2006): *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Rosko, M. D. (2001): "Cost Efficiency of US Hospitals: a Stochastic Frontier Approach." *Health Economics* **10(6)**: pp. 539–551.

Rosko, M. D. & J. A. Chilingerian (1999): "Estimating Hospital Inefficiency: Does Case Mix Matter?" *Journal of Medical Systems* **23:1**: pp. 57–71.

Sherman, D. H. (1984): "Hospital Efficiency Measurement and Evaluation. Empirical Test of a New Technique." *Medical Care* **22**: pp. 922–938.

Valdmanis, V. (1992): "Sensitivity Analysis for DEA Models An Empirical Example Using Public vs. NFP Hospitals." *Journal of Public Economics* **48**: pp. 185–205.

Vitaliano, D. F. & M. Toren (1996): "Hospital Cost and Efficiency in a Regime of Stringent Regulation." *Eastern Economic Journal* **22:2**: pp. 161–175.

Wagstaff, A. & G. Lopez (1996): "Hospital Costs in Catalonia: A Stochastic Frontier Analysis." *Applied Economics Letters* **3(7)**: pp. 471–74.

Worthington, A. C. (2004): "Frontier Efficiency Measurement in Health Care: A Review of Empirical Techniques and Selected Applications." *Med Care Res Rev* **61(2)**: pp. 135–170.

Yong, K. & A. Harris (1999): "Efficiency of Hospitals in Victoria under Casemix Funding: A Stochastic Frontier Approach." Working paper 92. Centre for Health Program Evaluation.

Zuckerman, S., J. Hadley, & L. Iezzoni (1994): "Measuring Hospital Efficiency with Frontier Cost Functions." *Journal of Health Economics* **13**: pp. 255–280.

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	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 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

						Rank correlation	
	obs.	mean	min	max	st.dev.	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: ≤ 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		With det.		Size	ID	Baseline		With determinants	
		eff.	rank	eff.	rank			eff.	rank	eff.	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						

IES Working Paper Series

2010

1. Petra Benešová, Petr Teplý : *Main Flaws of The Collateralized Debt Obligation's Valuation Before And During The 2008/2009 Global Turmoil*
2. Jiří Witzany, Michal Rychnovský, Pavel Charamza : *Survival Analysis in LGD Modeling*
3. Ladislav Kristoufek : *Long-range dependence in returns and volatility of Central European Stock Indices*
4. Jozef Barunik, Lukas Vacha, Miloslav Vosvrda : *Tail Behavior of the Central European Stock Markets during the Financial Crisis*
5. Onřej Lopušník : *Různá pojetí endogenity peněz v postkeynesovské ekonomii: Reinterpretace do obecnější teorie*
6. Jozef Barunik, Lukas Vacha : *Monte Carlo-Based Tail Exponent Estimator*
7. Karel Báťa : *Equity Home Bias in the Czech Republic*
8. Petra Kolouchová : *Cost of Equity Estimation Techniques Used by Valuation Experts*
9. Michael Princ : *Relationship between Czech and European developed stock markets: DCC MVGARCH analysis*
10. Juraj Kopecsni : *Improving Service Performance in Banking using Quality Adjusted Data Envelopment Analysis*
11. Jana Chvalkovská, Jiří Skuhrovec : *Measuring transparency in public spending: Case of Czech Public e-Procurement Information System*
12. Adam Geršl, Jakub Seidler : *Conservative Stress Testing: The Role of Regular Verification*
13. Zuzana Iršová : *Bank Efficiency in Transitional Countries: Sensitivity to Stochastic Frontier Design*
14. Adam Geršl, Petr Jakubík : *Adverse Feedback Loop in the Bank-Based Financial Systems*
15. Adam Geršl, Jan Zápal : *Economic Volatility and Institutional Reforms in Macroeconomic Policymaking: The Case of Fiscal Policy*

16. Tomáš Havránek, Zuzana Iršová : *Which Foreigners Are Worth Wooing? A Meta-Analysis of Vertical Spillovers from FDI*
17. Jakub Seidler, Boril Šopov : *Yield Curve Dynamics: Regional Common Factor Model*
18. Pavel Vacek : *Productivity Gains From Exporting: Do Export Destinations Matter?*
19. Pavel Vacek : *Panel Data Evidence on Productivity Spillovers from Foreign Direct Investment: Firm-Level Measures of Backward and Forward Linkages*
20. Štefan Lyócsa, Svatopluk Svoboda, Tomáš Výrost : *Industry Concentration Dynamics and Structural Changes: The Case of Aerospace & Defence*
21. Kristýna Ivanková : *Isobars and the Efficient Market Hypothesis*
22. Adam Geršl, Petr Jakubík : *Relationship Lending, Firms' Behaviour and Credit Risk: Evidence from the Czech Republic*
23. Petr Gapko, Martin Šmíd : *Modeling a Distribution of Mortgage Credit Losses*
24. Jesús Crespo Cuaresma, Adam Geršl, Tomáš Slačík : *Global Financial Crisis and the Puzzling Exchange Rate Path in CEE Countries*
25. Kateřian Pavloková : *Solidarita mezi generacemi v systémech veřejného zdravotnictví v Evropě*
26. Jaromír Baxa, Roman Horváth, Bořek Vašíček : *How Does Monetary Policy Change? Evidence on Inflation Targeting Countries*
27. Radovan Parrák, Jakub Seidler : *Mean-Variance & Mean-VaR Portfolio Selection: A Simulation Based Comparison in the Czech Crisis Environment*
28. Vladimír Benáček : *Aspekty efektivnosti při volbě profese a školy: Přizpůsobují se pražské střední školy potřebám podniků?*
29. Kamila Fialová : *Labor Institutions and their Impact on Shadow Economies in Europe*
30. Terezie Výprachtická : *Could the Stability and Growth Pact Be Substituted by the Financial Markets?*

2011

1. Roman Horváth, Jakub Matějů : How Are Inflation Targets Set?
2. Jana Procházková, Lenka Šťastná : Efficiency of Hospitals in the Czech Republic

Univerzita Karlova v Praze, Fakulta sociálních věd
Institut ekonomických studií [UK FSV – IES] Praha 1, Opletalova 26
E-mail : ies@fsv.cuni.cz http://ies.fsv.cuni.cz