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Efficiency of Hospitals in the Czech Republic: Conditional Efficiency Approach

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Abstract:

The paper estimates cost efficiency of 81 general hospitals in the Czech Republic during 2006-2010. We employ the conditional order-m approach which is a nonparametric method for efficiency computation accounting for environmental variables. Effects of environmental variables are assessed using the non-parametric significance test and partial regression plots. We find not-for-profit ownership and a presence of a specialized center in a hospital to be detrimental to hospital performance in the group of small and medium hospitals, while not-for-profit ownership is favorable to efficiency for big hospitals. Generally, hospital performance gets worse in period 2009-2010 because additional revenues received in form of user charges which were introduced in 2008 increase spending of hospitals. Only big hospitals proved to take some cost-saving measures as a reaction to financial crisis.

Keywords: efficiency, hospitals, conditional order-m FDH, Czech Republic
JEL: D24, I22

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1 Introduction

Efficiency of health-care provision has been of a major concern of all governments in the developed world. Health-care spending represents one of the largest government spending categories and it is not expected to shrink significantly due to more costly treatment of aging population. In the Czech Republic, over CZK 293 billion (7.63% of GDP) was spent on health care in 2012, and general government expenditure account for 84.18% of this amount (UZIS, 2014).

Measuring efficiency of hospitals has become widespread within individual countries in the last decades. Recent evidence is available from the United States (Bates *et al.*, 2006; Clement *et al.*, 2008; Nayar & Ozcan, 2008), Austria (Hofmarcher *et al.*, 2002), Switzerland (Farsi & Filippini, 2004), Great Britain (Jacobs, 2001), Netherlands (Blank & Valdmanis, 2010), Sweden (Janlov, 2007), Germany (Herr *et al.*, 2011; Herr, 2008) or Greece (Halkos & Tzeremes, 2011), to name a few. More examples can be found in overview studies by Hollingsworth (2008) or Worthington (2004).

Efficiency of hospitals—the way they transform inputs into outputs—may be affected by environmental factors, which are beyond the scope of hospitals' management. Operating in a good/bad environment increases/decreases hospital's efficiency. Hence, environmental factors should be taken into account in the efficiency estimation (Blank & Valdmanis, 2010).

In non-parametric estimations, there are several ways to account for environmental variables (see e.g. Fried *et al.* (2008)) The conditional efficiency approach (originally developed by Cazals *et al.* (2002), extended by Daraio & Simar (2005) and DeWitte & Kortelainen (2013)) has been lately recognized as the most suitable approach to account for environmental variables in non-parametric analyses. We follow the conditional efficiency model formulated in DeWitte & Kortelainen (2013) that allows us to distinguish between continuous and discrete environmental variables and, at the same time, does not require separability between the environmental and input-output spaces (exogenous variables may influence the production process).

In the sphere of health care, Halkos & Tzeremes (2011) applies conditional efficiency to health-care provision in Greek regions. However, to our knowledge, this study is the first one computing conditional efficiency of hospitals. The paper also extends previous research on Czech hospitals (non-parametric analyses in Dlouhý *et al.* (2007) and Novosadova & Dlouhy (2007) which did not account for environmentals at all; and a parametric analysis in our previous research in Votapkova & Stastna (2013)) by using the best known non-parametric method and by covering more recent and more appropriate data on outputs not available before (Diagnostic-Related-Groups, DRG, reflecting the severity of treated patients).

The paper estimates cost efficiency of 81 general hospitals in the Czech Republic during 2006–2010. We focus on inpatient care and evaluate how the total inpatient costs are transformed to outputs which include the total number of patients treated at acute wards weighted by the DRG case-mix index, patients treated at nursing wards and publications produced. Publication output reflects not only research production, but also involvement in teaching, when especially university hospitals with higher inpatient costs support research activities.

We employ a non-parametric significance test and partial regression plots to uncover the significance and the direction of the effect of environmental variables, such as ownership, presence of highly specialized center, cost conditions, or specific time effects. We found not-for-profit ownership status and a presence of a specialized center in a hospital to significantly decrease efficiency within the group of small and medium hospitals. On the contrary, not-for-profit ownership status increases efficiency of big hospitals. Additionally, efficiency worsens in the last two years of our observation since additional revenues received in the form of user charges directly from patients (legislative change in January 2008) make hospitals to spend more. Still cost-saving measures as a reaction to financial crisis are observed in 2010 for big hospitals.

This paper is organized as follows. Section 2 provides theoretical background for conditional efficiency analysis and describes the methodology of the non-parametric significance test and partial regression plots. Section 3 presents the dataset and introduces variables employed. Section 4 presents the results and Section 5 concludes and provides motivation for further research.

2 Methodology

To assess efficiency of hospitals in the Czech Republic, (i) we apply the conditional order-m efficiency model accounting for both discrete and continuous exogenous characteristics as proposed by DeWitte & Kortelainen (2013), and (ii) we use a nonparametric bootstrap procedure to draw statistical inference for the environmental variables on the ratio of conditional to unconditional efficiency scores developed by Racine & Li (2004) and Li & Racine (2004). Since the significance test does not provide any information about the direction of influence, (iii) we employ methodology of Daraio & Simar (2005, 2007) and use partial regression plots to visualize the direction of the effects of environmental variables.

2.1 Conditional order-m efficiency model

Consider a production technology with a set of all feasible input-output combinations $\Psi = \{(x, y) \in \mathbb{R}_+^{p+q} | x \text{ can produce } y\}$, where $x \in \mathbb{R}_+^p$ is a vector of inputs and $y \in \mathbb{R}_+^q$ is a vector of outputs. The best practice frontier follows from Ψ, which is freely disposable, but unknown in reality, and has to be estimated from a random sample. Let $N = (1, \ldots, n)$ be the set of decision-making units (DMUs) in the dataset. We analyze the problem from the input-oriented perspective and study how inputs can be contracted given the output level, because hospital management has greater control over the costs than outputs.

In our analysis, we do not use traditional Free Disposal Hull (FDH) estimator of efficiency, where the best-practice frontier envelopes all the data and hence is very sensitive to extreme values. Instead, we employ partial frontier model (order-m), in which observations may lie above the frontier.[1] The notion of an order-m frontier rests on drawing a random subset of m observations out of N for each DMU $i \in N$ that at least produce the output level

[1] We avoid the assumption of convexity of Ψ. As pointed out by Daraio & Simar (2007), there is no reason to assume convexity, they find the convexity assumption in the order-m estimation useful only if it serves as a robustness check of a convex attainable set.

y_i. The resulting minimum, i.e. the frontier input level for output level y_i, is obtained as the average of the minimum input levels of the randomly drawn m observations. As m approaches to n, order-m estimator approaches to the FDH estimator. The higher m is, the more comparable observations we take into account, however, the optimal value of m should be set when the percentage of points lying above the frontier stabilizes (Cazals *et al.*, 2002). The rate of convergence of the order-m estimator to its true value is unusually fast considering non-parametric statistics.

We follow the probabilistic formulation of the production process, in which we incorporate external environmental variables exogenous to the production process itself but explaining possibly a part of it, as first proposed by Cazals *et al.* (2002) for the case of one environmental variable and extended by Daraio & Simar (2005) to the multivariate case.

Similar to Daraio & Simar (2005), we examine a probability that an evaluated observation defined by (x, y)—conditioned on a given value of $Z = z$, where $\mathbf{Z}$ is vector of environmental characteristics—is dominated by another observation. The joint probability function, given $Z = z$, is defined as:

$$H_{XY|Z}(x, y|z) = Pr(X \leq x, Y \geq y|Z = z) \tag{1}$$

which may be decomposed into:[2]

$$\begin{aligned} H_{XY|Z}(x, y|z) &= Pr(X \leq x|Y \geq y, Z = z)Pr(Y \geq y|Z = z) \\ &= F_{X|Y,Z}(X \leq x|Y \geq y, Z = z)S_{Y|Z}(Y \geq y|Z = z) \\ &= F_{X|Y,Z}(x|y, z)S_{Y|Z}(y|z), \end{aligned} \tag{2}$$

where $F_{X|Y,Z}$ denotes a cumulative distribution function of X and $S_{Y|Z}$ is the conditional survivor function of Y.[3] Supposing the existence of conditional probabilities $S_{Y|Z}(y|z) > 0$, we can define Ψ^z with the support of $F_{X|Y,Z}$ for all y, where $\Psi^z \subseteq \Psi$. Ψ^z is described such that (Daraio & Simar, 2007):

$$\Psi^z = \{(x', y) \in \mathbb{R}_+^{p+q} | x' \geq x^{\partial,z}(y) \text{ for } (x, y) \in \Psi\}, \tag{3}$$

where $x^{\partial,z}(y)$ is the efficient level of input, conditional on $Z = z$, for an output level y: $x^{\partial,z}(y) = \theta(x, y|z)x$, where $(x, y) \in \Psi$ and $\theta(x, y|z)x$ is the Farrell measure of input-oriented efficiency score for a unit operating at the level (x, y) and in an environment z. Note that $\theta(x, y|z)$ and $x^{\partial,z}(y)$ are non-decreasing in y.

The lower boundary of $F_{X|Y,Z}$ then defines the input-oriented Farrell efficiency frontier for a unit with output level y producing in an environment z, i.e.:

$$\theta(x, y|z) = \inf\left\{\theta | F_{X|Y,Z}(\theta x|y, z) > 0\right\} \tag{4}$$

Before obtaining a non-parametric estimator of efficiency, $\theta(x, y|z)$ in (4), smoothing in z due to equality in $Z = z$ is necessary. Having done so, a non-parametric kernel estimator of

[2] Observations in the sample are denoted by lowercase letters, while random variables are denoted by uppercase letters.

[3] The distribution is non-standard due to the condition $Y \geq y$ instead of $Y = y$ condition (see Daraio & Simar (2007) for further explanation).

$F_{X|Y,Z}(.|y,z)$ defined in (5) is plugged into (4) (Daraio & Simar (2007):

$$\hat{F}_{X|Y,Z} = \frac{\sum_{i=1}^{n} I(x_i \leq x, y_i \geq y) K((z - z_i)/h)}{\sum_{i=1}^{n} I(y_i \geq y) K((z - z_i)/h)}, \tag{5}$$

where $I(\cdot)$ denotes the indicator function, $K(\cdot)$ is the kernel and h is the bandwidth parameter which needs to be estimated using an appropriate algorithm. The estimator of efficiency is obtained as (Daraio & Simar, 2005):

$$\begin{aligned} \hat{\theta}_m(x,y|z)| &= \hat{E}_{X|Y,Z}(\theta_m(x,y)|Y \geq y, Z = z) \qquad (6) \\ &= \int_0^{\infty} [1 - \hat{F}_X(ux|y,z)]^m du \end{aligned}$$

The estimator $\hat{\theta}_m(x,y|z)$ asymptotically converges to a deterministic conditional FDH estimator (Cazals *et al.*, 2002), thus preserving its asymptotic properties. $\hat{\theta}_m(x,y|z)$ is estimated n times, once for each DMU. Note that, by definition, it does not necessarily hold that $\forall i$, $\hat{\theta}_m(x,y|z) \in \langle 0, 1 \rangle$. If $\hat{\theta}_m(x,y|z) < 1$, there is a scope for reduction of inputs of the DMU relative to the average inputs of the randomly drawn reference set. If $\hat{\theta}_m(x,y|z) > 1$, the DMU on average performs better than the randomly drawn reference set. Even though order-m efficiency estimator is less sensitive to extreme values (see Cazals *et al.* (2002)), if $\hat{\theta}_m(x,y|z) \gg 1$, it may either indicate an outlier or an observation deserving a particular attention.

Even though the curse of dimensionality cannot be completely avoided in the conditional order-m efficiency estimation due to the dimension in Z which slows down the rate of convergence compared to the unconditional case as claimed by Daraio & Simar (2005), DeWitte & Kortelainen (2013) show that the convergence rates of the estimators do not depend on the number of discrete, but only on the number of continuous variables in Z.

Following DeWitte & Kortelainen (2013), in order to estimate the Kernel function in (5), we redefine the components of the multivariate $\mathbf{Z}$, such that $z_i = (z_i^c, z_i^o, z_i^u)$, $i = 1, \ldots, n$, where $z_i^c \in \mathbb{R}^r$ is a vector of continuous environmental variables, $z_i^o \in \mathbb{R}^v$ is a vector of ordered discrete variables and $z_i^u \in \mathbb{R}^w$ is a vector of unordered discrete variables. Discrete variables may take on more than two values. Standard multivariate product kernel function is used to smooth each of the groups of variables. The generalized product kernel function is obtained as a multiplication of the above, such that:

$$K(z, z_i, h) = \prod_{s=1}^{r} \frac{1}{h_s^c} l^c\left(\frac{z_s^c - z_{is}^c}{h_s^c}\right) \prod_{s=r+1}^{r+v} l^o(z_s^o, z_{is}^o, h_s^o) \prod_{r+v+1}^{r+v+w} l^u(z_s^u, z_{is}^u, h_s^u) \tag{7}$$

where $l^c(\cdot), l^o(\cdot)$ and $l^u(\cdot)$ are univariate kernel functions and h_s^c, h_s^o and h_s^u are bandwidths for continuous, ordered and unordered environmental variables, respectively. For continuous variables, we use Epanechnikov kernel which has a compact support, i.e. $k(z) = 0$ if $|z| \geq 1$, Aitchison & Aitken (1976) is used for discrete univariate kernel functions for unordered discrete variables and Li & Racine (2007) for ordered discrete variables. As a method of bandwidth selection for both continuous and discrete variables, we once again follow DeWitte & Kortelainen (2013) and apply the least squares cross–validation method (Badin *et al.*, 2010) based on the closely related conditional probability density functions as suggested by Li &

Racine (2008) and developed by Hall *et al.* (2004). By this approach, observation specific optimal bandwidths for each z-variable are obtained.

2.2 Nonparametric significance test

To find out the influence of environmental variables on the production process, we compare the conditional efficiencies $\hat{\theta}_m(x, y|z)$ in (6) with unconditional efficiencies $\hat{\theta}_m(x, y)$.[4]

Following DeWitte & Kortelainen (2013) we use kernel weighted local linear least squares, a non-parametric regression technique developed by Racine & Li (2004) which smooths both continuous and discrete variables, again without sample splitting. Furthermore, this methodology avoids imposing any parametric assumptions. Consider a non-parametric model:

$$\hat{Q}_i^z = \tilde{f}(z_i) + \epsilon_i, \quad i = 1, \ldots, n \tag{8}$$

where $\hat{Q}_i^z = \frac{\hat{\theta}_m(x_i, y_i|z_i)}{\hat{\theta}_m(x_i, y_i)}$, ϵ_i is the error term uncorrelated with environmental variables $[E(\epsilon_i|z_i) = 0]$, and $\tilde{f} = \tilde{\alpha} - (z_i^c - z^c)\tilde{\beta}$ represents the conditional mean function of the estimated ratio $\hat{Q}_i^z$. The following local linear least squares minimization problem has to be solved:

$$\min_{\alpha,\beta} \sum_{i=1}^{n} (\hat{Q}_i^z - \tilde{\alpha} - (z_i^c - z^c)\tilde{\beta})^2 K((z - z_i)/h), \tag{9}$$

where α and β are local linear estimators to be obtained, such that $\hat{\alpha} = \hat{\alpha}(z)$ and $\hat{\beta} = \hat{\beta}(z^c)$ and are consistent estimators of the true conditional mean function $f(z) = E(Q^z|z)$ and the gradient $\beta(z^c) = \frac{\partial E(Q^z|z)}{\partial z^c}$. Additionally, $K(\cdot)$ is the generalized product kernel function as in (7) and h is the bandwidth vector again estimated by the least-squares cross-validation method (Li & Racine, 2004).

Note that not only does the bias resulting from the estimated dependent variable disappears asymptotically, but the framework does not suffer from any other inference problems (see Simar & Wilson (2007)) as a traditional two-stage FDH or DEA analysis.[5]

Having estimated the conditional mean functions and the gradients for each unit, we test significance of each continuous and discrete variable (Racine, 1997; Racine *et al.*, 2006). The tests are non–parametric equivalents to standard t-tests in Ordinary Least Squares, however according to Racine *et al.* (2006), they are more general because they test both linear and nonlinear relationships.[6]

2.3 Partial Regression Plots

Even though non-parametric tests reveal significant influence of z-variables on $\hat{Q}_i^z$, they do not provide any information about the direction of influence. We follow Daraio & Simar (2005, 2007) and DeWitte & Kortelainen (2013) and use estimates from (8). In our multivariate

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[4]Methodology for unconditional efficiency measures $\hat{\theta}_m(x, y)$ is obtained analogically, for details see for instance Daraio & Simar (2007)

[5]For details see also DeWitte & Kortelainen (2013).

[6]Refer to Racine (1997) and Racine *et al.* (2006) for details on hypotheses and test statistics.

setting, we picture partial regression plots such that we plot $\hat{Q}_i^z$ against one variable fixing all other variables (at the median).[7]

The interpretation of the regression line (in case of input orientation) is the following:

(i) If the regression line is increasing, vector Z is detrimental (unfavorable) to efficiency. According to Daraio & Simar (2005), environmental variable here acts like 'extra' undesired output requiring more inputs in the production activity, hence Z exerts a negative effect on the production process. Unconditional efficiency is lower for larger values of Z—hence, $\hat{Q}_i^z$ will increase on average with Z.

(ii) If the regression line is decreasing, then Z is conductive (favorable) to efficiency. Here, the environmental variable works as a 'substitutive' input to the production process, allowing the DMU to save inputs in the production process. Unconditional efficiency is greater for larger values of Z—hence, Q_i^z will decrease when Z increases.

3 Data

There were 189 hospitals of in-patient and out-patient care in the Czech Republic in 2010. Out of the total, 19 hospitals were run by Ministry of Health (including 10 university hospitals), there were 24 regional and 17 municipal hospitals, 121 private hospitals (major shareholder was region or municipality for 53 hospitals), 3 church hospitals and 5 hospitals run by other state bodies (including military hospitals and hospitals for prisoners). Out of 189 hospitals, there were 30 hospitals with only nursing care.

Hospitals are mainly reimbursed by health insurance funds for the health care provided.[8] Money that hospitals receive from health insurance funds covers both reimbursement for care and capital investment. Hospitals have been increasingly paid by funds on the basis of the DRG-payment scheme since 2007, reaching 85 % of all hospital reimbursement in 2013. User charges that hospitals receive directly from the patients is an additional income that they are free to use as they want.

State-owned or regional and municipal hospitals also receive money from the state budget, thus general taxation. Money from the state budget is often used to cover long-term investment projects (Ministry of Finance, 2014). Private and corporatized hospitals do not receive such state contributions.

In the paper, data on 81 general hospitals for the period 2006–2010 was analyzed. Out of 159 general hospitals, 61 hospitals were excluded for various reasons: some of the hospitals

[7] Naturally, discrete ordered variables must be evaluated at their levels (categories) to obtain the average effect, and, average effect cannot be deduced for unordered discrete variables. Effects of unordered discrete variables have to be evaluated at the particular data point.

[8] The largest part of the Czech health-care expenditure is financed from the statutory health insurance which is deducted from wages of economically active individuals. Health insurance of economically inactive individuals (children, students, pensioners, parents on maternity leave, prisoners, etc.) is paid for by the state. The contributions are collected to the pool and, based on a risk-adjustment scheme, consequently redistributed among 7 health insurance funds operating in the Czech Republic. Every citizen has to be insured with one of the 7 health insurance funds. Health insurance funds purchase health services on behalf of their insurees. Any private health insurance plan has been absent in the Czech Republic.

were closed, were parts of a larger legal entity not reporting separate data, or did not report data at all. Outlier-detection analysis as of Wilson (1993) and careful visual inspection of the data, excluded additional 17 observations.[9] The final unbalanced panel consists of 395 observations. The number of observations in each cross-section varies from 81 in 2009 and 2010 to 77 in 2007 and 2008. 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' 59,000 patients a year. The distribution of hospitals in terms of average size is depicted in Figure 1.

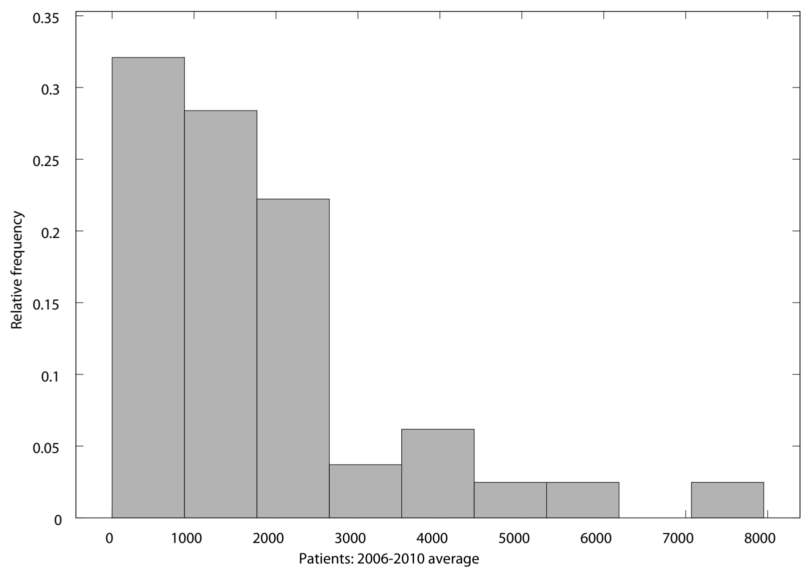

Figure 1. Distribution of hospitals

Data on individual hospitals was obtained from various sources,[10] data expressed in monetary terms, i.e. costs and salaries, was adjusted for inflation using annual growth rate of inflation with base year 2006. All analysis was estimated with R 2.14.0 (R Development Core Team, 2006), adapting the code of DeWitte & Kortelainen (2013).

3.1 Input and output variables

The analysis focuses on cost efficiency of inpatient care in hospitals. Inpatient care consumes majority of hospital resources as found by Yong & Harris (1999) and it is more suitable for the analysis due to data availability. For the Czech hospitals, inpatient costs represent around

[9]Three observations would have significantly distorted the frontier and the remaining hospitals revealed inconsistency in operating-cost reporting in the period examined.

[10]Most of the data was obtained from the Institute of Health Information and Statistics of the Czech Republic (further 'UZIS'); Narodni referencni centrum (further 'NRC') provided us with data on Diagnostic-Related Groups (further 'DRG'); the Web of Science was used to retrieve data on publications affiliated to the particular hospital. Data on environmental characteristics was obtained from the Czech Statistical Office, Registry of Companies of the Czech Republic and the Ministry of Health.

50% of total costs on average. Outpatient care accounts for 15–20% of total costs, the rest is taken up by transportation costs and non-medical expenses.

The only input variable in the analysis is total operating costs (*costs*) which comprise all inpatient costs excluding capital costs. It was calculated as multiplication of operating costs per patient day, the number of admissions and the average length of stay (all publicly 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.[11]

Outputs refer to in-patients only (we do not take into account ambulatory patients). Prior to the analysis, we first divided the number of patients into acute care and nursing care.[12] Costs on acute care and nursing care significantly differ, thus this division is crucial for the efficiency analysis; furthermore, DRG case-mix index reflecting the severity of cases is available for acute care only. Hence, we end up with two outputs related directly to inpatient care: (i) the number of acute care patients adjusted for the DRG case-mix index (*acute*), and (ii) the number of patients in nursing care (*nursing*) assuming that costs per patient in nursing care should not differ too much across individual hospitals.

Furthermore, we believe that university hospitals incur additional costs for inpatient care because of teaching and research. Teaching hospitals are usually pioneers of new, but expensive, technologies, to be able to teach their students the latest progress in medicine. When the students practice a particular step or operation, they are provided with real–life material which however is sometimes spoiled. Very often, there are professors who, besides teaching responsibilities, work as doctors in teaching hospitals and thus come across new research questions, which they then publish.

Unfortunately, data on the number of students/graduates affiliated to a particular university hospital which would reflect demanding nature of teaching is unavailable. Hence, we focus on research activity and include variable accounting for publications of a hospital. This variable may however to some extent also reflect teaching activities of a hospital, as bigger hospitals where more students are affiliated are more likely to publish more research results. Assuming that primarily big and university hospitals carry out research, it is believed to improve low relative efficiency scores of a group of big and university hospitals as found in our previous research.

The third output variable (*publish*) is obtained as the first principal component of the data retrieved from the Web of Science database where inputs to the principal component analysis are (i) articles, (ii) meeting abstracts, (iii) letters, reviews, proceedings papers, all

[11] The data was adjusted for inflatin with 2006 representing the base year.

[12] Disaggregated data to acute and nursing care was available only for 2009 and 2010, however shares of nursing and acute care did not significantly differ between the two years, so we applied the shares of 2009 for total number of patients in years 2006–2008.

weighted by the share of domestic authors affiliated to the particular hospital.[13] We applied positive affine transformation to avoid negative values and the minimum was added to all observations in the sample. The first principal component explains 64.45% of information in the publication data. Table 1 presents outcome of the principal component analysis.[14]

Table 1. Principal component analysis

	PC1	PC2	PC3
Eigenvalue	1.934	0.994	0.072
Proportion	0.645	0.331	0.024
Cumulative	0.645	0.976	1.000
Components' loadings			
Journal articles	0.706	0.021	0.708
Monographs	0.698	0.149	−0.700
Other publications	0.120	−0.989	−0.091

3.2 Environmental characteristics

Environment in which hospitals operate may influence their efficiency. Hospitals may be managed differently when they are joint-stock companies instead of not-for-profit institutions; hospitals in the capital city may face different costs of labor and material than hospitals in peripheral locations; hospitals with highly specialized treatment may incur higher costs, etc.

In 2004 a process of corporatization of Czech hospitals with the main purpose of more efficient resource allocation started and many hospitals were transformed from not-for-profit institutions into joint-stock companies. However, even corporatized hospitals are effectively under the public control since regions, district or municipalities are their major shareholders. Having carefully examined individual hospitals, it has been found that only 5% of for-profit hospitals in the sample are owned by a private entity. Hence, it is hard to control for the effect of ownership (private versus public) for for-profit hospitals. Therefore, we consider only the not-for-profit status (*not_profit*) using a dummy variable taking the value of 1 when a hospital is public not-for-profit and 0 otherwise, i.e. when a hospital is for-profit (95% of them are effectively public). We expect not-for-profit hospitals to be less efficient than for-profit hospitals.

Additionally, we account for the fact whether a specialized center is situated in a hospital and include a dummy variable for the presence of a specialized center (*specialization*), as of a list obtained from the Czech Ministry of Health. Highly specialized treatment may be on

[13] Including individual types of publications separately would unreasonably increase dimensionality. Including just one type of publication always discriminates a portion of hospitals.

[14] We performed the analysis also for different specifications of publication output. We firstly considered only journal articles from the Web of Science database, however some hospital were found to produce more proceedings papers and their publication output would be then undervalued. In addition, we took into account publications from the Czech research and innovations database, however data is available only for university hospitals and other hospitals receiving a grant from the Czech Ministry of Education.

one hand connected with increased costs, which would decrease relative efficiency. On the other hand, doctors involved in specialized treatment may have higher publication activity which would increase relative efficiency. The effect of this variable on efficiency will depend on which of these two directions overweight. There are 26 hospitals (corresponding to 114 observations in the pooled panel) with a specialized center in our sample.

Out of the covered period 2006–2010, the efficiency in the last two years 2009 and 2010 could be influenced by two factors. The more important one is the legislative change which came into force in 2008 introducing user charges for each inpatient day in a hospital and for outpatient visits, both regularly and emergency.[15] Higher revenues soften budget constraint for a hospital which may then afford higher operational costs. In such a case, we would expect decrease of efficiency in these two years.

On the contrary, fiscal stress that spread due to the world financial crisis is assumed to work mostly in an opposite direction. Hospitals as well as other public and private institutions are forced to save money due to limited public financial support, hence their costs should be lower (efficiency for given outputs should increase). However, a hospital could also affect its output and let the patients stay only for the mimimum time necessary to recover (efficiency for given input would decrease). These two actions may also balance out resulting in no special effect upon efficiency.

We include a year dummy taking the value of 1 for 2009 or 2010, and zero otherwise (*2009_2010*), (Model 1). Additionally, to find out whether there might be a delayed effect of the crisis specific to year 2010, we consider two separate year dummies (*2009*) and (*2010*), taking the value of 1 if observed in the respective year and zero otherwise (Model 2). The effect of the dummy will show whether hospitals were affected by the fiscal crisis, or whether user charges made up for the lower financial support resulting from government savings.

Finally, we have to take into account that hospitals may face different cost conditions. We include average monthly salary in the district (*salary)* to proxy the price of labor and partly general price level in the district affecting the price of goods and services purchased by the hospitals.[16] Descriptive statistics of all variables is provided in Table 2.

4 Empirical results

In this section, we present empirical results. Firstly, we check whether we can pool the panel data and carry out a cross–sectional analysis. If a pooled cross–sectional analysis is reasonable - i.e. if the frontier is stable in time - we construct a single frontier and simultaneously compare hospitals among one another and observations across time.

We carry out a preliminary unconditional efficiency analyses for each year and for a pooled dataset. We check poolability of the panel using the Spearman's rank correlation coefficient

[15]We assume that the effect of 2008 user charges may be dealyed to 2009.

[16]The Czech Statistical Office provides data for districts (76 districts in total plus the capital city) only till 2004. From 2005 on, such a detailed data is not available anymore and we can use only more aggregated data for 14 regions. Therefore, for the years covered in the analysis, data from 2004 was adjusted for respective annual growth of the average wage in the region in years 2005–2010. This approximation is considered to be sufficient for the analysis. The data was adjusted for inflation with 2006 representing the base year.

Table 2. Descriptive statistics

	Variable type	Mean	Median	Minimum	Maximum	St.dev.
costs	continuous	6.23E+08	3.38E+08	6.19E+07	3.84E+09	7.83E+08
acute	continuous	21,606.08	12,409.53	1,730.255	126,906.8	25,014.44
nursing	continuous	250.1733	175.3564	0	1177.914	276.4222
publish	continuous	0.473663	0	0	9.877884	1.374565
not_profit	non–ordered discrete	0.549367	1	0	1	0.497557
specialization	non–ordered discrete	0.288608	0	0	1	0.453115
2009_2010	non–ordered discrete	0.407595	0	0	1	0.491387
2009	non–ordered discrete	0.202532	0	0	1	0.401886
2010	non–ordered discrete	0.205063	0	0	1	0.403748
salary	continuous	19,294.61	18,375.87	15,630.66	27,198.06	2,757.03

between single year scores and the scores from the pooled dataset. Correlations vary from 0.73 in 2010 to 0.87 in 2007 and reveal a considerable time stability except for the lower values of coefficients in 2009 and 2010 (coefficients 0.76 and 0.73, respectively), which will be tested in the main analysis.

We performed unconditional and conditional order-m Free Disposal Hull analyses on a pooled dataset. In conditional analysis, we account for environmental characteristics in which hospitals operate, hence compared to the unconditional efficiency score, the conditional efficiency score of a particular hospital is lower/higher if the hospital operates in favorable/detrimental environment. Concerning conditional analysis, we construct two different models: (i) Model 1 accounts for a joint dummy variable taking the value of one if observed in 2009 or 2010, whereas (ii) Model 2 uses two separate dummy variables for each year 2009 and 2010.

Every non-parametric efficiency analysis is highly sensitive to outliers. Holding $m = 100$[17] to obtain the order-m scores (hence each observation out of 395 is compared to a random set of 100 observations), only 18 observations score above 1.1, 10 score above 1.2 and 1 above 1.4 in the unconditional efficiency model, however in the conditional efficiency model, there is no such an observation. Excessively large efficiency value would suggest that an observation lies far above the frontier. Thus, we successfully got rid of all the potential outliers in the initial analysis and do not detect any outliers in the current sample.

Summary of efficiency scores for an unconditional model ($\hat{\theta}(x, y)$) and conditional efficiency model ($\hat{\theta}(x, y|z)$) for the pooled dataset is provided in Table 3. Efficiency scores for two alternative specifications of conditional model—Model 1 and Model 2—are very similar (Spearman's/Pearson's correlation coefficients are 0.9793/0.9922), hence we present summary of scores only from Model 1.

Mean of both unconditional and conditional efficiencies of the whole sample is considerably high, reaching 0.90 and 0.95, respectively. Hence, a hospital can save on average 10% of its costs when compared to a random set of 100 other observations producing at least the same

[17]Low volatility with respect to $m = 100$ was revealed. Other values of m were tested (Badin *et al.*, 2012).

level of output. An average hospital is however constrained by the operational environment, hence savings of around only 5% should be sufficient.

Policymakers are often interested how efficiency differs for hospitals of different sizes. Even though size effect did not prove significant in the non-parametric significance test, we disaggregate the sample of hospitals according to size to uncover if there indeed is no difference in efficiency for small and big hospitals. Small (big) hospitals treat less (more) than 10,000 (20,000) patients a year on average, medium hospitals treat 10,000–20,000 patients a year on average. Boundaries for the size groups were determined from the frequency distribution of hospitals covered in our sample based on the condition that all groups should contain similar number of observations for a disaggregated analysis to be feasible.

Unconditional and conditional mean efficiencies increase as the size of a hospital increases (Table 3). This however does not fully hold for the value of median which is the lowest for medium hospitals. On one hand, there are a few small hospitals with a very low scores pulling down the mean value, and on the other hand, there are some medium hospitals with very high efficiency score pulling up its mean value. Generally it seems that big and small hospitals are more efficient than medium hospitals. Big hospitals are those having higher publication output and small hospitals may face harder budget constraints.

Table 3. Summary of efficiency scores

	Whole sample		Small		Medium		Big	
	$\hat{\theta}(x,y)$	$\hat{\theta}(x,y\|z)$	$\hat{\theta}(x,y)$	$\hat{\theta}(x,y\|z)$	$\hat{\theta}(x,y)$	$\hat{\theta}(x,y\|z)$	$\hat{\theta}(x,y)$	$\hat{\theta}(x,y\|z)$
Min	0.358	0.416	0.358	0.457	0.426	0.416	0.547	0.648
Max	1.418	1.023	1.237	1.023	1.418	1.009	1.238	1.008
Mean	0.901	0.953	0.868	0.927	0.904	0.957	0.933	0.976
Median	0.949	1	0.943	1	0.919	1	1	1
St. dev.	0.169	0.114	0.202	0.144	0.167	0.110	0.117	0.065
Efficiency ≥ 1	155	294	51	96	39	100	65	98
Efficiency ≥ 1.1	18	0	5	0	9	0	1	0
Efficiency ≥ 1.2	10	0	3	0	6	0	1	0
Efficiency ≥ 1.4	1	0	0	0	1	0	0	0
No. obs.	395	395	136	136	134	134	125	125

Note: No separate benchmark was created for size groups.

Conditional efficiency controls for several environmental variables which are beyond scope of hospital management. To uncover whether the variables have significant effect upon efficiency and hence are the right ones to include in the conditional efficiency estimation, we perform a non-parametric significance test. Since the direction of influence cannot be retrieved from the test, we simultaneously analyze partial regression plots.[18] Table 4 presents results for the whole sample. It reveals average of observation-specific bandwidths for each

[18] Recently, means how to uncover whether environmental variables affect the distribution of efficiency scores or whether they are cost frontier shifters have been developed (Badin *et al.*, 2012, 2014). Such an analysis is, however, beyond scope of this paper.

environmental variable used to smooth the kernel function in the conditional efficiency estimation and illustrates whether an environmental variable has favorable or detrimental effect (i.e. increasing or decreasing) upon efficiency (based on partial regression plots which are available in the Appendix).

Table 4. Effects of environmental variables: whole sample

	Model 1				Model 2			
	P-value		Banwth	Effect	P-value		Banwth	Effect
not_profit	0.126	†	0.1003	favorable	0.126	†	0.3063	favorable
specialization	0.008	***	0.2050	favorable	< 2e-16	***	0.0830	favorable
2009					0.048	**	0.1247	unfavorable
2010					0.010	**	0.2068	unfavorable
2009_2010	< 2e-16	***	0.2068	unfavorable				
salary	0.192	†	652.17	mixed	0.714		646.25	mixed

Notes: signif. codes – 0.01 '***' 0.05 '**' 0.1 '*', one-tail '†'; 'Banwth' denotes bandwidths.

Alternative specifications in Model 1 and Model 2 provide robust results. Effect of the not-for-profit dummy variable is surprisingly favorable, hence if a hospital is not-for-profit it tends to be more efficient than the for-profit one. However, this variable is significant only on one-tail. The effect may be caused by the fact that big hospitals mostly with not-for-profit status are more often involved in research than other hospitals, hence having higher publication output. Similarly, higher publication output is an obvious reason why hospitals with specialized center tend to be more efficient than other hospitals. (Correlation coefficient between publication output and specialization dummy is 0.52.)

The joint dummy variable for 2009 and 2010, as well as, both of the two separate dummies exert a significant unfavorable influence on the performance of Czech hospitals, hence efficiency in these two years is lower when compared to previous years 2006–2008. Additional revenues from user charges seem to influence costs but not outputs of our analysis. We, however, cannot say that hospitals waste more money, as these financial resources may contribute to higher quality of treatment not measured by outputs in our analysis. Partial regression plots in Figure A1 show a consistent effect for years 2009 and 2010.

Results further suggest that cost conditions do not influence the performance of a hospital significantly. The fact that wages of doctors and nurses are regulated by the state in public hospitals may explain this surprising finding.

To uncover whether effects of environmental variables are specific to size of a hospital and to provide a robustness check of the results, we carry out separate conditional analyses for two homogeneous groups:(i) big hospitals and (ii) small and medium hospitals. Results of the analyses are provided in Table 5.

Table 5. Effects of environmental variables: big, small and medium hospitals

Big hospitals									
	Model 1				Model 2				
	P-value		Banwth	Effect	P-value		Banwth	Effect
not_profit	0.042	**	0.0028	favorable	0.056	*	0.0000	favorable
specialization	0.116	†	0.2083	favorable	0.002	***	0.2909	unfavorable
2009					0.002	***	0.1769	unfavorable
2010					0.008	***	0.1677	favorable
2009_2010	0.038	**	0.0139	unfavorable				
salary	0.990		489.42	mixed	0.208		4579.06	mixed
Small and medium hospitals								
	Model 1				Model 2			
	P-value		Banwth	Effect	P-value		Banwth	Effect
not_profit	< 2e-16	***	0.4093	unfavorable	0.062	*	0.3745	unfavorable
specialization	0.010	***	0.0161	unfavorable	0.042	**	0.1468	unfavorable
2009					0.098	*	0.2032	unfavorable
2010					0.406		0.2438	unfavorable
2009_2010	0.012	**	0.1878	unfavorable				
salary	0.778		321.01	mixed	0.544		293.38	mixed

Notes: signif. codes – 0.01 '***' 0.05 '**' 0.1 '*', one-tail '†'; 'Banwth' denotes bandwidths.

Concerning big hospitals, results of the Model 1 with the joint dummy for years 2009 and 2010 are consistent with the aggregate results, only significance of the specialization dummy is not as strong. If we, however, analyze separate effects for years 2009 and 2010 (Model 2), the results change dramatically. Specialization dummy turns out to decrease efficiency, hence big hospitals with specialized center have higher costs (not balanced out by higher publication output) which make them less efficient. Effect of dummy for year 2010 reveals that big hospitals were probably forced to take some cost-saving measures as a reaction to the financial crisis, because their efficiency tends to increase in 2010.[19]

Results for small and medium hospitals show an interesting pattern. Contrary to the aggregate analysis, hospitals with not-for-profit status tend to have lower efficiency within the group of small and medium hospitals. Hence, it seems that privatization of hospitals fulfilled its purpose to increase efficiency. Additionally, hospitals with specialized center tend to have lower efficiency as they incur higher costs and do not involve in research as much as big hospitals with specialized centers. Models 1 and 2 provide consistent results and it seems that hospitals spent more due to higher revenues from user charges in 2009 and 2010; hence, contrast to big hospitals, small and medium hospitals did not react to fiscal crisis and did not decrease their spending significantly in 2010.

[19]Data supports this conclusion as costs are higher for big hospitals in 2009 than in 2010—means are very similar, however median is CZK 1.012 billions in 2009 and CZK 985 millions in 2010, maximum is CZK 3.75 billions in 2009 and CZK 3.67 billions in 2010.

5 Conclusion

This paper examined cost efficiency of inpatient care of 81 general hospitals in the Czech Republic in the period 2006–2010. The number of acute care patients adjusted for severity of cases using the DRG-case-mix index, the number of nursing patients and publications of hospitals represented outputs. Operational costs was the only input entering the analysis. Following the methodology of DeWitte & Kortelainen (2013), non-parametric conditional order-m FDH analysis was carried out. We control for the following environmental variables: a dummy for not-for-profit ownership status, a dummy for the presence of a specialized center, a dummy for years 2009 and 2010 (effect of additional revenues in form of user charges vs. financial crisis), and cost conditions. As in DeWitte & Kortelainen (2013) and Nieswand (2013), significance of the environmental variables was assessed using the non-parametric significance test and partial regression plots were used to retrieve the direction of influence of the environmental variables. To uncover whether effects of environmental variables were specific to size of a hospital and to provide a robustness check of the results, we carried out a separate conditional analysis for big hospitals and small and medium hospitals.

Mean of both unconditional and conditional efficiencies of the whole sample is considerably high, reaching 0.90 and 0.95, respectively. Hence, a hospital can save on average 10% of its costs. However, when controlled for operational environment, saving of around only 5% is sufficient.

In the analysis of the whole sample, we found that not-for-profit ownership status is favorable to efficiency. This effect was opposite to what we expected as one of the arguments for privatization and making hospitals for-profit organizations was to increase their efficiency. When we study the effects for big hospitals and small and medium hospitals separately, we found that the favorable effect holds only for big hospitals. Big hospitals with not-for-profit status are more often involved in research and have higher publication output. On the contrary, small and medium hospitals with not-for-profit status were found to be less efficient within the group of small and medium hospitals, hence the argument for privatization holds in this case.

Hospitals with specialized centers have on one hand higher costs, but on the other hand they often report higher publication output. Although in the analysis for the whole sample, we got a clear favorable effect upon efficiency (higher publication output outweighs higher costs), in separate analyses, the effects are not as clear. Small and medium hospitals with specialized centers seem not to produce enough publications and hence tend to be less efficient (higher costs outweigh publication output) than other small and medium hospitals without such centers. Effect for big hospitals is not robust across two specifications.

Additionally, we analyzed whether efficiency in years 2009 and 2010 was affected by (i) the introduction of user charges in 2008, (ii) fiscal stress which spread due to the world financial crisis when hospitals were forced to save money due to limited public financial support. We found that the factor (i) was much stronger and additional revenues made hospitals to spend more, i.e. efficiency of hospitals in 2009 and 2010 was lower. Results of separate analyses suggest that only big hospitals tried to take some significant cost-saving measures in 2010 as a reaction to financial crisis.

Surprisingly, we did not find any significant effect of cost conditions upon efficiency. The fact that wages of doctors and nurses are regulated by the state in public hospitals may explain this surprising finding.

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Appendix

Figure A1. Partial regression plots: whole sample

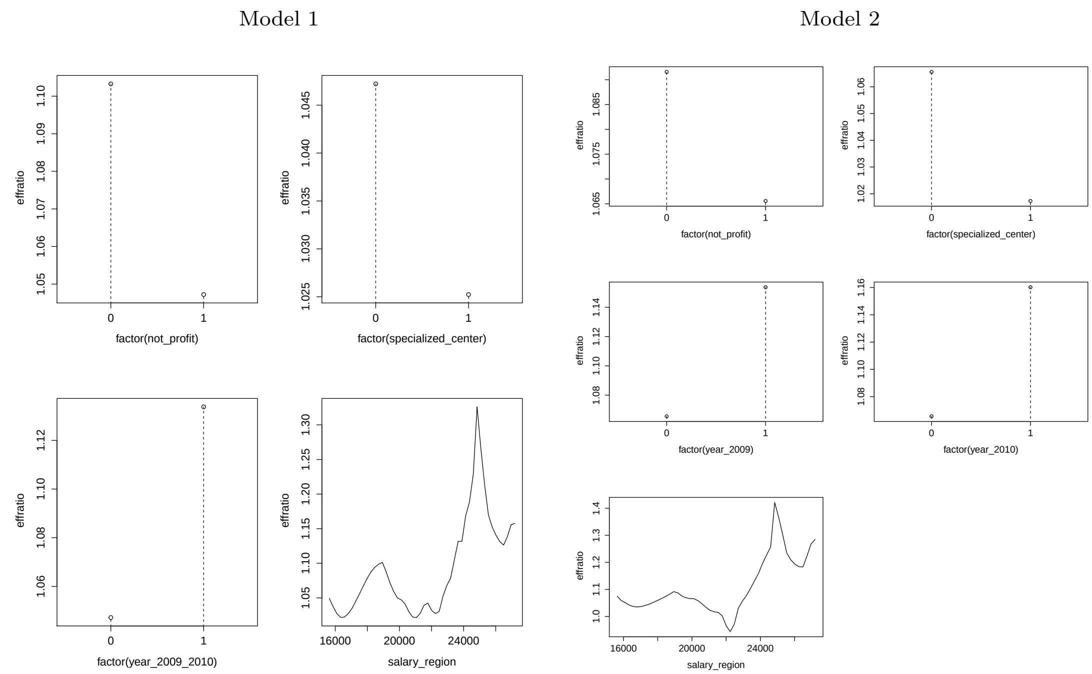


Figure A2. Partial regression plots: small and medium hospitals

Model 1 Model 2

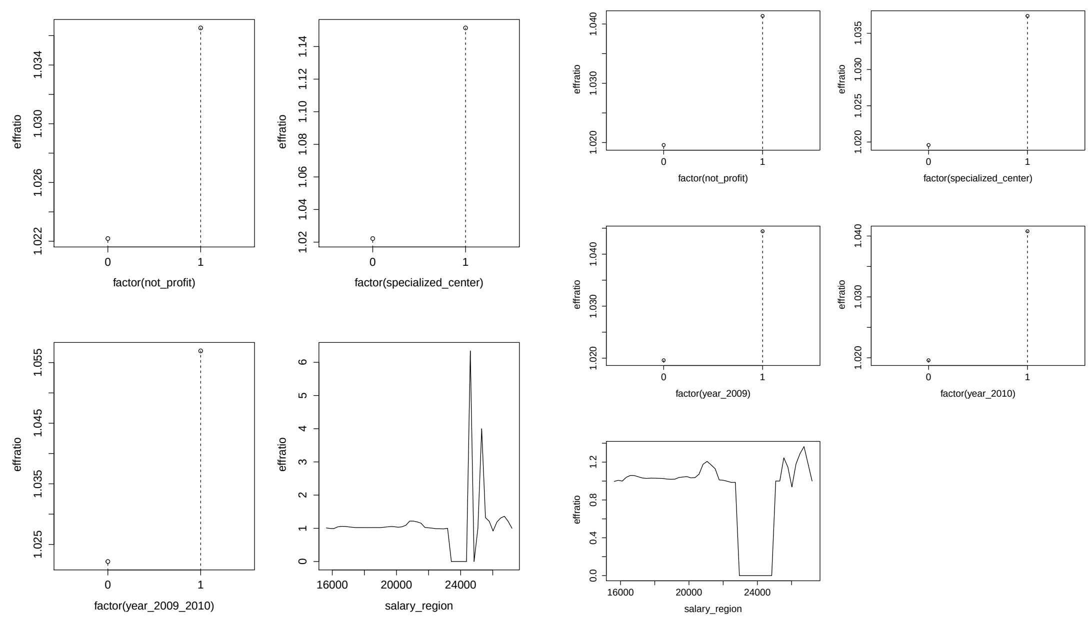
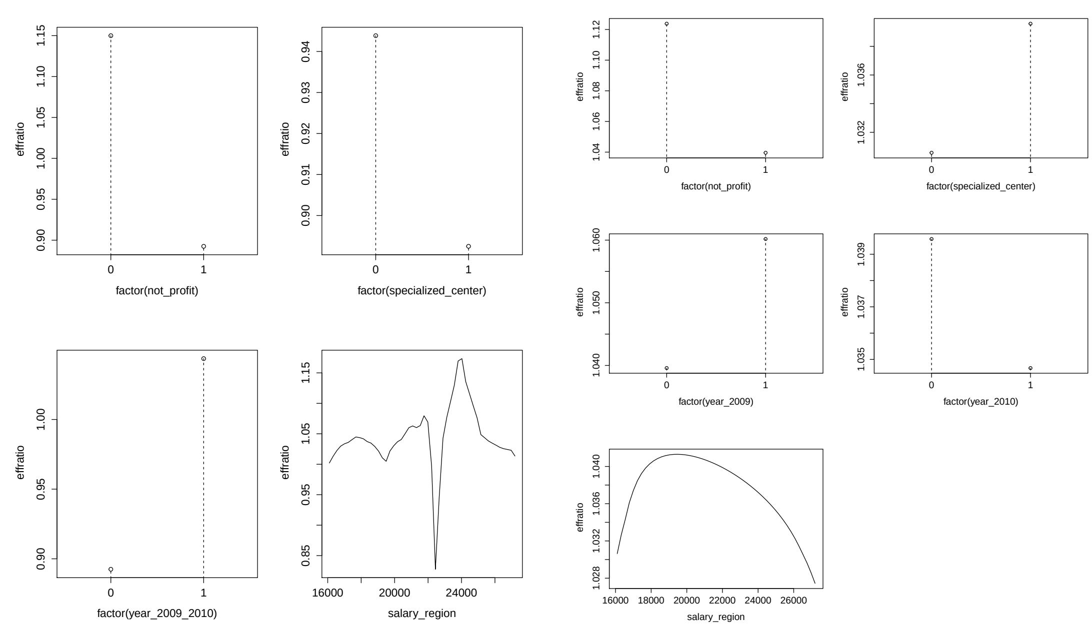


Figure A3. Partial regression plots: big hospitals

Model 1 Model 2



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