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# Efficiency of hospitals in the Czech Republic: Conditional efficiency approach

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**Abstract**
This paper estimates the cost efficiency of 81 general hospitals in the Czech Republic during 2006–2010. We employ the conditional order-*m* approach to assess how inpatient costs in a hospital translate to inpatient outputs considering its environmental characteristics. The outputs include quantitative indicators such as (i) acute patients adjusted for DRG case-mix index, (ii) nursing patients, and (iii) publications reflecting research activity of a hospital; but also a qualitative indicator (iv) nurses/bed ratio. Nonprofit hospitals, university hospitals, and hospitals with specialized centers are generally less efficient.

**Keywords** Efficiency · Hospitals · Conditional order-m · Czech Republic

## 1 Introduction

The efficiency of healthcare provision has been of major concern for all governments in the developed world. Healthcare spending is one of the largest government spending categories and it is expected to grow because of population aging. The Czech Republic is not an exception. The Czech government has introduced a number of reforms to increase the efficiency of the healthcare system. The corporatization of hospitals starting in 2004 should have reduced public cost due to more effective management of financial resources. The introduction of regulatory fees in 2008 should have increased private participation in healthcare expenses and reduced the excessive use of cost-free health services.[1] Despite reforms to increase private participation in healthcare expenses, out of almost CZK 292 billion (7.96% of GDP) spent on healthcare in 2010, general government expenditure amounted to 83.3% (Institute of Health Information and Statistics of the Czech Republic [IHIS], 2011) which shifts the Czech Republic among OECD countries with the highest share of government spending on healthcare.

The global economic crisis puts hospitals under additional financial pressure. Due to high unemployment rates, the amount of mandatory wage-based health insurance contributions decreased, thus reduced the amount available for the healthcare system since wage-based contributions represent the primary source of financing this system. This resulted in hospitals receiving less money, although revenues of hospitals traditionally increase over time. Hence, measures to evaluate the efficiency of healthcare spending and success of the reforms may have important policy implications.

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[1] The Czech healthcare system is a statutory health insurance system with obligatory wage-based contributions. Private participation is minimal. To decrease the unnecessary overuse of cost-free healthcare services, user charges were introduced in January 2008. Patients were charged for physician visits, for every item on a drug prescription, for each day of inpatient care, and for emergency services, however, fees were not sizeable amounting from approximately one to four euros. Due to political debates and controversies, user charges were slowly being phased out from April 2009 until end of 2014, with the exception of an emergency care visit. User charges for inpatient care were already abolished in January 2014).

The aim of this paper is to evaluate the efficiency of hospitals in the Czech Republic during 2006–2010 and explain differences in efficiency based on several hospitals' characteristics. Measuring the efficiency of hospitals has become widespread within individual countries in the last decades. Recent evidence is available from Portugal (Ferreira and Marques 2016; Ferreira et al. 2018), Germany (Tiemann and Schreyögg 2012), Greece (Halkos and Tzeremes 2011), Netherlands (Blank and Valdmanis 2010), Nordic countries (Linna et al. 2010). Varabyova et al. (2017) compare efficiency of hospitals in Italy and Germany. Efficiency is assessed also for hospitals in the U.S. (Bates et al. 2006; Clement et al. 2008; Nayar and Ozcan 2008), Sweden (Janlöv 2007), Switzerland (Farsi and Filippini 2006), Austria (Hofmarcher et al. 2002), or Great Britain (Jacobs 2001). More examples can be found in a recent overview of studies by Kohl et al. (2018) and in earlier works by Hollingsworth (2008) or Worthington (2004).

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

In non-parametric estimations, there are several ways to account for environmental variables (see e.g. Fried et al. 2008). As is shown in Simar and Wilson (2007), traditional two-stage approaches suffer from several problems (see for example Matranga et al. (2014), Tiemann and Schreyögg (2012) for applications of two-stage approaches in health care). Even though Simar and Wilson (2007) propose a method to overcome complications of two-stage approaches (for example Araújo et al. (2014) analyzing Brazilian hospitals follow their approach), we recognize merits of a one-stage conditional efficiency approach (originally developed by Cazals et al. (2002), extended by Daraio and Simar (2005, 2007)) most suitable to account for environmental variables in the efficiency analysis of Czech hospitals. We follow the conditional efficiency model 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.

In the sphere of healthcare, analyses applying the conditional-efficiency approach are rare. Halkos and Tzeremes (2011) apply conditional efficiency to healthcare provision in Greek regions, Cordero et al. (2015) analyze primary care providers using a conditional approach, Varabyova et al. (2017) use a conditional approach to compare efficiency in Italian and German hospitals. Hence, this paper is among a few healthcare studies applying a conditional efficiency model. In addition, the paper extends previous research on Czech hospitals—non-parametric analyses in Dlouhý et al. (2007) and Novosádová and Dlouhý (2007) who did not account for environments at all, and a parametric analysis in Votapkova and Stastna (2013)—by using the most appropriate non-parametric method and by covering more recent and better data on outputs not available before (Diagnostic-Related-Groups, DRG, reflecting the severity of treated patients, which is currently being developed in the Czech Republic).

In this paper, we focus on inpatient care and evaluate how the total inpatient costs are transformed into 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 the number of nurses per one bed which represents a qualitative indicator of treatment. On top of that, we include the number of weighted publications similar to Linna and Häkkinen (1998) and Linna (1998) to reflect not only research production, but also involvement in teaching, especially when university hospitals with higher inpatient costs support research activities.

We aim to explain differences in efficiency using a set of environmental variables, such as nonprofit ownership, presence of highly specialized centers, teaching status (university hospital), occupancy rate or specific time effects. A non-parametric significance test and partial regression plots are employed to uncover the significance and the direction of the effect of these variables. We find that nonprofit hospitals, university hospitals, and hospitals with specialized centers have generally lower efficiency. Additionally, efficiency worsens in the years 2009–2010 since additional revenues received in the form of user charges directly from patients allowed hospitals to spend more and loosen their budget constraints—the effect was strong particularly for nonprofit hospitals.

This paper is organized as follows. Section 2 provides the 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 the variables employed. Section 4 presents the results and Section 5 concludes.

## 2 Methodology

Consider a production technology with a set of all feasible input $x \in \mathbb{R}_+^p$ and output $y \in \mathbb{R}_+^q$ and denote $Z \in \mathbb{R}_+^d$ several environmental factors exogenous to the production process itself, but which may explain a part of it. Following Cazals et al. (2002) and Daraio and Simar (2005), the unconditional (marginal) attainable set of feasible combinations of inputs and outputs, $\Psi = \{(x, y) \in \mathbb{R}_+^{p+q} | x \text{ can produce } y\}$ can be characterized by $\Psi = \{(x, y) | H_{X,Y}(x, y) > 0\}$, where $H_{X,Y}(x, y) = \text{Prob}(X \leq x, Y \geq y)$. So $\Psi$ is the support of the joint random variable $(X, Y)$. The best practice frontier follows from $\Psi$, 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, because hospital management has greater control over inputs than outputs.

From the frontier literature it is known that, assuming free disposability of inputs and outputs, the unconditional (marginal) input oriented Farrell-Debreu technical efficiency of a production plan $(x, y)$, may be defined as:

$$\theta(x,y) = \inf\{\theta|(\theta x,y) \in \Psi\} = inf\{\theta|S_{X|Y}(\theta x|y) > 0\}, \quad (1)$$

where $S_{X|Y}(x|y) = \text{Prob}(X \leq x|Y \geq y)$ is the nonstandard conditional survival function of $X$ given that $Y \geq y$.

For conditional efficiency measures we define the attainable set $\Psi^z \subset \mathbb{R}_+^{p+q}$ as the support of the conditional probability:

$$H_{X,Y|Z}(x,y|z) = \text{Prob}(X \leq x, Y \geq y|Z = z).$$

Accordingly, the conditional input oriented technical efficiency of a production plan $(x, y) \in \Psi^z$, facing conditions $z$, is defined in Daraio and Simar (2005) as:

$$\theta(x,y|z) = \inf\{\theta|(\theta x,y) \in \Psi^z\} = \inf\{\theta|S_{X|Y,Z}(\theta x|y,z) > 0\}, \quad (2)$$

where $S_{X|Y,Z}(x|y, z) = \text{Prob}(X \leq x|Y \geq y, Z = z)$.

Nonparametric estimators of the attainable sets can be obtained by plugging nonparametric estimators of the survivor functions in the definitions above. Plugging the empirical version of $S_{X|Y,Z}$ in (2) provides the popular FDH (Free Disposal Hull) estimator of $\Psi$. A nonparametric estimator of the conditional survival function $S_{X|Y,Z}(x|y, z)$ could be obtained by using standard smoothing methods where a bandwidth $h$ has to be determined for each component of $(Z)$.

Daraio and Simar (2005, 2007) and Bădin et al. (2010) discuss in detail how to choose the appropriate bandwidths. They are determined by the estimation of conditional distributions $S_{X|Y,Z}(x|y, z)$, where we condition on $Y \geq y$ and a particular value of $Z = z$ and here standard tools from Hall et al. (2004) and Li and Racine (2008) can be adapted. Of course here only the variables $(z)$ require smoothing and appropriate bandwidths, since we have:

$$\hat{S}_{X|Y,Z}(x|y,z) = \frac{\sum_{i=1}^{n} 1(x_i \leq x, y_i \geq y) K_{h_z}(z_i)}{\sum_{i=1}^{n} 1(y_i \geq y) K_{h_z}(z_i)}, \quad (3)$$

where the functions $K_{h_z}(z_i)$ are kernels (see Bădin et al. (2010) for technical details).[2]

In order to estimate the conditional distributions in (3), we redefine the components of the multivariate $Z$ to include discrete variables (Bădin et al. 2010, 2012), such that $z_i = (z_i^c, z_i^u)$, $i = 1, \ldots, n$, where $z_i^c \in \mathbb{R}^v$ is a vector of continuous environmental variables, and $z_i^u \in \mathbb{R}^w$ is a vector of unordered discrete variables.[3] The generalized product kernel function is obtained as a multiplication of the standard multivariate product kernel functions of each of the groups of variables, such that:

$$K_{h_z}(z_i) = \prod_{s=1}^{r} K^c_{h^c_s}(z^c_s - z^c_{is}) \prod_{s=r+1}^{r+w} K^u_{h^u_s}(z^u_s, z^u_{is}) \quad (4)$$

where $K^c_{h^c_s}(\cdot)$ and $K^u_{h^u_s}(\cdot)$ are univariate kernel functions and $h^c_s$ and $h^u_s$ are bandwidths for continuous and unordered discrete environmental variables, respectively. For continuous variables, we use Epanechnikov kernel which has a compact support, i.e. $K^c_{h^c_s}(z^c_s - z^c_{is}) = 0$ if $|z| \geq 1$ and Aitchison and Aitken (1976) is used for discrete univariate kernel functions for unordered discrete variables. As a method of bandwidth selection for both continuous and discrete variables, we apply the least squares cross-validation method (Bădin et al. 2010, 2012) based on the closely related conditional probability density functions as suggested by Li and Racine (2008) and developed by Hall et al. (2004).[4]

These nonparametric estimators are consistent with rate $n^{1/(p+1)}$ and Weibull limiting distribution for the unconditional FDH (see Park et al. 2000). For the conditional case, we have similar results where $n$ is replaced by $nh^d$ where $d$ is the dimension of all the conditioning variables $(Z)$, so $d = r + p + 2$ (see Jeong et al. 2010). So the rates of convergence of the conditional estimators are deteriorated by the dimension $d$.

In applied studies, the application of these nonparametric techniques may be problematic because the presence of outliers or extreme data points in real data samples, which fully determine the estimated frontier and the measurement of inefficiencies, are totally unrealistic. To solve this problem, approaches have been proposed in the frontier literature (Cazals et al. 2002; Daouia and Simar 2007) to keep all the observations in the sample but to replace the frontier of the empirical distribution by (conditional) quantiles or by the expectation of the minimum (or maximum) of a subsample of the data. This latter method defines the order-$m$ frontier that we will use here.

To be short, the partial output-frontier of order-$m$ is defined for any integer $m$ and for an output $y$, as the expected value of the minimum of the input of $m$ units

[2] Optimal bandwidths can be selected by Least Squares Cross-Validation (LSCV) or by Maximum Likelihood Cross-Validation, which are asymptotically equivalent, see e.g. Li and Racine (2007).

[3] The model may be extended to also include ordered discrete variables (DeWitte and Kortelainen, 2013).

[4] The bandwidth refers to vector of bandwidths containing individual bandwidths for each variable.

drawn at random from the populations of firms producing more output than $y$. Formally:

$$\theta_m(x,y) = \mathbb{E}\left[\min_{1,\dots,m}\left\{\max_{j=1,\dots,p}\left(\frac{X_i^j}{x^j}\right)\right\}\right], \tag{5}$$

where the $X^j$ are independently distributed as $S_{X|Y}(\cdot|Y \geq y)$. The same applies for the conditional order-$m$ frontier where the $X^j$ are distributed as $S_{X|Y,Z}(\cdot|Y \geq y, Z = z)$. Nonparametric estimators are obtained by plugging the nonparametric estimators of the survival functions in (5).

Cazals et al. (2002) show that, when $m$ increases and converges to $\infty$, the order-$m$ frontier and its estimator converge to the full frontier. For a finite $m$, the frontier will not envelop all the data points and so is much more robust than the FDH to outliers and extreme data points.[5] Another advantage of these estimators is that they achieve the parametric rate of convergence $\sqrt{n}$ and that they have a normal limiting distribution.

## 2.1 Impact of environmental variables on the production process

To find out the influence of environmental variables on the production process, we follow the procedure described in Bădin et al. (2012) and we will compare estimates of $\theta_m(x, y|z)$ with those of $\theta_m(x, y)$, i.e. using 'conditional' and 'unconditional' efficiency scores. The procedure allows disentangling the potential effects of environmental variables on the boundary (shift of the frontier) and on the distribution of the inefficiencies (see Bădin et al. 2012; Mastromarco and Simar 2015). The first effect can be investigated by considering the ratios of conditional to unconditional efficiency measures, which are measures relative to the full frontier of the conditional and the unconditional attainable sets, respectively. As illustrated in Daraio and Simar (2007), some extreme or outlying data points may hide the real effect of $Z$, so it is suggested to do the analysis with order-$m$ frontier, with large values of $m$ to get robust estimates of the full frontier. In this case, the ratios to be analyzed are given by:

$$\hat{R}_i^z = \frac{\hat{\theta}_m(x_i, y_i|z_i)}{\hat{\theta}_m(x_i, y_i)} \tag{6}$$

As stated in Bădin et al. (2012), the full frontier ratios, or their robust version with large values of $m$, indicate only the influence of $Z$ on the shape of the frontier, whereas the partial frontiers for small values of $m$, characterizes the behavior of the shift more in the center of the distribution of efficiencies, inside the attainable sets.[6] A tendency of the ratios to decrease with the conditioning variables indicates a favorable effect of these variables on the distribution of the efficiencies and the opposite in the case of an unfavorable effect.[7]

We have a sample of $n$ pairs $(z_i, \hat{R}(x_i, y_i|z_i)), i = 1, \dots n$, in the nonparametric model, we estimate the local average of $\hat{R}(x_i, y_i|z_i)$, the localization of which is determined by the bandwidth $h$ (see Bădin et al. 2014). Following Racine and Li (2004) and Daraio and Simar (2014) we use kernel weighted local linear least squares, a non-parametric regression technique which smoothes both continuous and discrete variables without sample splitting.[8]

The following local linear least squares minimization problem has to be solved:

$$\min_{\hat{\alpha},\hat{\beta}} \sum_{i=1}^{n} (\hat{R}_i^z - \hat{\alpha}(z_i) - \hat{\beta}(z_i))^2 K_{h_z}(z_i), \tag{7}$$

where $\hat{\alpha}$ and $\hat{\beta}$ are local linear estimators to be obtained, such that $\hat{\alpha} = \hat{\alpha}(z)$ and $\hat{\beta} = \hat{\beta}(z)$ are consistent estimators of the true conditional mean function $f(z) = E(Q^z|z)$ and the gradient $\beta(z) = \frac{\partial E(Q^z|z)}{\partial z}$. Additionally, $K_{h_z}(\cdot)$ is the generalized product kernel function as in (4) and $h_z$ is the bandwidth vector again estimated by the least-squares cross-validation method (Li and Racine 2004).

Then we test significance of each continuous and discrete variable (Racine 1997; Racine et al. 2006).

## 2.2 Partial regression plots

We follow Daraio and Simar (2005, 2007) and visualize the effects of $Z$ in partial regression plots. In our multivariate setting, we plot $\hat{R}_i^z$ against one variable fixing all other variables (at the median).

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 and Simar (2005), the 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.

[5] Daouia and Gijbels (2011) analyze these estimators from a theory of robustness perspective.

[6] For instance if $m = 1$, the order-$m$ frontier turns out to be an average production function and the ratios (6) would analyze the shift of the mean of the distribution of the inefficiencies.

[7] As explained in Bădin et al (2012), the ratios are not bounded by 1, because the order-$m$ efficiency scores are not bounded by 1.

[8] Note that Li et al (2016) propose a complete smoothing technique which allows for different bandwidth parameters for continuous variables in different categories of the discrete variables.

Unconditional efficiency is lower for larger values of $Z$—hence, $\hat{R}_i^z$ will increase on average with $Z$.

(ii) If the regression line is decreasing, then $Z$ is conducive (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, i.e. environmental factors inherently reduce the amount of inputs hospitals require to treat their patient base. Unconditional efficiency is greater for larger values of $Z$—hence, $R_i^z$ will decrease when $Z$ increases.

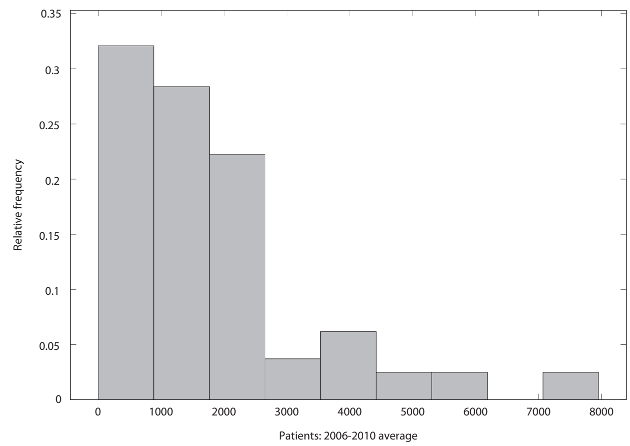


**Fig. 1** Distribution of hospitals by size

## 3 Data

Data on 81 general hospitals for the period 2006–2010 was analyzed. From the total number of Czech general hospitals, 36% were excluded for various reasons: some of the hospitals were closed, incorporated into larger entities, or did not report data. 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 389 observations. The number of observations in each cross-section varies from 75 in 2007 and 2008 to 81 in 2010. 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 treats only 59,000 patients a year. The distribution of hospitals in terms of average size is depicted in Fig. 1.

Data on individual hospitals was obtained from multiple sources,[10] data expressed in monetary terms, i.e. costs and salaries, was adjusted for inflation using an annual growth rate of inflation with base year 2006. Results were estimated with R 2.14.0 (R Development Core Team 2006).

### 3.1 Input and output variables

The analysis focuses on the cost efficiency of inpatient care in hospitals. Inpatient care consumes the majority of hospital resources as found by Yong and Harris (1999) and it is more suitable for the analysis due to data availability. For Czech hospitals, inpatient costs represent around 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 the multiplication of operating costs per inpatient day, the number of admissions, and the average length of stay (all publicly available from IHIS, 2006–2010). IHIS (2006–2010) calculates operating costs per inpatient day, $C$, as:

$$C = C_{In} \times \frac{1 + \frac{C_T + C_O + C_N}{C_{In} + C_{Out}}}{D},$$

where $C_{In}$ are costs for inpatient care, $C_T$ costs for medical transport, $C_O$ costs for other medical care, $C_N$ costs for non-medical procedures, $C_{Out}$ outpatient costs and $D$ number of inpatient days.

The most important output for hospital efficiency analysis is the number of patients (only inpatients in our case, not outpatients) which is often used in the literature and which is preferred to inpatient days that may bias the results due to possible endogeneity born by the length of stay (see Zuckerman et al. 1994; Farsi and Filippini 2006; Hofmarcher et al. 2002).

Prior to the analysis, we first divided the number of patients into acute care and nursing care, because costs on acute care and nursing care significantly differ.

Cases within nursing care are rather homogeneous, but within acute care some hospitalizations are more expensive than others. Not accounting for this may lead to bias in efficiency measurement (Ferreira and Marques 2016; Bruning and Register 1989; Burgess and Wilson 1995). Weighting outputs according to case-mix has been acknowledged as vital, particularly when the sample consists of hospitals of different sizes, or university hospitals together with other acute hospitals, to minimize intra-

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

[10] The data was obtained from the Institute of Health Information and Statistics of the Czech Republic (IHIS, 2004, 2005, 2006–2010); Narodni referencni centrum ('NRC') provided us with data on Diagnostic-Related Groups ('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.

hospital as well as inter-hospital differences (Chowdhury et al. 2014; Rosko and Chilingerian 1999; Valdmanis 1992; Hofmarcher et al. 2002).

Case-mix adjustment has to capture essential structural differences between hospitals (Anthun et al. 2017). Different case-mix criteria appear in the literature, such as diagnostic-related groupings (Chowdhury and Zelenyuk 2016; Hofmarcher et al. 2002; Vitaliano and Toren 1996; Magnussen 1996); service-mix index (Ferreira and Marques 2016) which is similar to the case-mix index but easier to compute; the types of patients treated (Kooreman 1994), or country-specific weights (Chowdhury et al. 2014).

Often case-mix is used as a weighting device, but sometimes case-mix is used as a separate output (Grosskopf and Valdmanis 1993; Kooreman 1994; Rosko and Chilingerian 1999). Note that the choice of weighting criteria influences the distribution of efficiency scores (Anthun et al. 2017; Magnussen 1996; Chowdhury et al. 2014) or may shift the frontier per se (Ferreira and Marques 2016). Different methods in case-mix adjustment were tested on Portuguese hospitals in Ferreira and Marques (2016), including case-mix adjustment and service-mix adjustment. Interestingly, Ferreira and Marques (2016) find out that proper environmental correction may strongly substitute for case-mix adjustment, but obviously at higher costs for the researcher. Case-mix adjustment of patients proved vital even when the efficiency of a specific treatment (lung cancer) was compared among hospitals in Beck et al. (2018).

Case-mix is used as a weighting device of acute inpatient care in this paper. We end up with two outputs related directly to inpatient care: (i) the number of acute care patients weighted for the DRG case-mix index (*acute_DRG*), and (ii) the number of patients in nursing care (*nursing*).

The more nurses attend one bed per day, the higher the quality of care is expected. The number of nurses per available bed (*nurse_bed*) thus represents a qualitative indicator which is used as a separate output in the analysis, similar to Beck et al. (2018). We are aware of the potential bias when the number of nurses is excessively large, driving the value-added on quality of the additional nurse to zero. This is not the case of Czech hospitals, which more often face shortages of nurses.

University hospitals incur additional costs for inpatient care because of teaching and research. Not only is the presence of students costly, but university hospitals are usually pioneers of new, but expensive technologies, to be able to teach their students the latest progress in medicine. Oftentimes, there are professors who, besides working as doctors, teach and are involved in research.

Data on the number of students/graduates affiliated with a particular university hospital could reflect the demanding nature of teaching, but unfortunately it is not available. Hence, we focus on research activity and include a variable accounting for publications by a hospital. Assuming that primarily big and university hospitals carry out research, publication output should improve low relative efficiency scores of a group of big and university hospitals found in Votapkova and Stastna (2013).

There has been a wide discussion in the literature whether to include a "teaching variable" among outputs or among environmental variables (e.g. Vitaliano and Toren 1996; Rosko and Chilingerian 1999; Rosko 2001, etc.). Since hospitals themselves decide how much they will be involved in research activities, publications will be included among outputs similar to Linna (1998) and Linna et al. (1998) to reflect another kind of output which a hospital can control and which cannot be captured by the volume and case-mix variables (Vitaliano and Toren 1996).

The fourth 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[11] are (i) articles, (ii) meeting abstracts, (iii) letters, reviews, proceedings papers, all weighted by the share of domestic authors affiliated to the particular hospital.[12]

We applied the 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, while weights assigned to journal articles and monographs are almost the same. Table 1 presents the outcome of the principal component analysis.

### 3.2 Environmental characteristics

The environment in which hospitals operate may influence their efficiency. Hospitals may be managed differently when they are joint-stock companies instead of nonprofit institutions; university hospitals provide a different structure of services; hospitals with highly specialized treatment may incur higher costs in general.

In 2004, a process of corporatization of Czech hospitals started, the main purpose of which was to allocate resources

[11] Principal component analysis (PCA) transforms a large set of variables into a lower set of linearly uncorrelated values called principal components which best explain the variance in the data (Pearson, 1901).

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

**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 |

Components' loadings of each variable explains the correlation between the particular component and the variable. Squared loading of each variable is then the proportion of the variance of the variable explained by the particular component

more efficiently. Many hospitals were transformed from nonprofit 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 hospital's ownership (private versus public) with only a few observations of private ownership. Therefore, we consider only the nonprofit status (*nonprofit*) using a dummy variable taking the value of 1 when a hospital is public nonprofit and 0 otherwise.

We expect nonprofit hospitals to be less efficient than for-profit hospitals since the objective of for-profit hospitals in the Czech Republic is (i) to control financial flows and not to create losses due to stricter budget constraints (nevertheless, for-profit hospitals with a public authority as a major shareholder may ask for easing their debt under certain circumstances). Another objective of for-profit hospitals should be to (ii) increase technical efficiency. Thus, wards with low occupancy are often closed down. On the contrary, smaller public nonprofit hospitals more often keep wards that are not fully used to guarantee access of care. In the Czech environment, however, specialized and teaching hospitals belong to nonprofit hospitals to guarantee them some sort of assurance of stability, but specialization and teaching variables are controlled for in the analysis.

We include a dummy variable for the presence of a specialized center (*specialization*) in a hospital, as of a list obtained from the Czech Ministry of Health.[13] Highly specialized treatment may be on one hand connected with increased costs (not entirely captured by DRG adjusted output), 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 are overweight. There are 26 hospitals (corresponding to 114 observations in the pooled panel) with a specialized center in our sample.

Besides publishing results of research (captured in outputs), university hospitals reveal a different structure of services providing less basic and more highly-specialized care, management, and organization of resources (Vitaliano and Toren 1996). Costs of university hospitals are often higher than costs in other hospitals (Grosskopf et al. 2001b). University hospitals also suffer from congestion, i.e. excess use by residents. Grosskopf et al. (2001b) discovered that about 20% of inefficiency of university hospitals is caused by congestion. Grosskopf et al. (2001a) carries out a comparison of the technical efficiency of university and non-university hospitals finding out that "only about 10% of university hospitals can effectively compete with other hospitals based on provision of patients' services."

University status (*university*) included among determinants in this paper captures how the 'historic mission' affects a hospital's position vis-a-vis the best practice production frontier. The status of university hospital is assumed to exert a negative pressures on efficiency.

Occupancy rate (*occupancy*) defined as the ratio of the actual inpatient days to the maximum inpatient days possible, captures whether the hospital operates below its potential capacity. Higher occupancy rate is expected to exert a positive effect on efficiency because hospitals face fixed costs connected with each bed available.

Out of the covered period 2006–2010, the efficiency of the last two years 2009 and 2010 could be influenced by two factors. The more important 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 regular and emergency.[14] Higher revenues soften budget constraints for a hospital, which may then afford higher operating costs. In such a case, we would expect a 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 the opposite direction. Hospitals as well as other public and private institutions are forced to save money, hence their costs should be lower (efficiency for given outputs should increase). These two contradictory effects may also balance out resulting in no special effect upon efficiency.

We include a dummy variable taking the value of 1 for 2009 or 2010, and zero otherwise (*2009_2010*). The effect of the dummy will show whether hospitals were affected by

[13] Examples include Oncology centres, rheumatology centres, ophthalmology centres, etc.

[14] We consider the effect of increased revenues to be delayed to 2009 as hospitals need some leeway to respond to this increase.

**Table 2** Descriptive statistics

| | Mean | Median | Min | Max | St.Dev. |
|---|---|---|---|---|---|
| Costs (thousands CZK) | 629,000 | 338,000 | 61,900 | 3,840,000 | 788,000 |
| Acute_DRG | 21,755.10 | 12,426.28 | 1730.26 | 126,906.80 | 25,155.90 |
| Nursing | 249.867 | 175.356 | 0 | 1,177.914 | 276.308 |
| Nurse_bed | 0.522 | 0.504 | 0.271 | 1.291 | 0.112 |
| Publish | 0.480 | 0 | 0 | 9.878 | 1.384 |
| Nonprofit | 0.545 | 1 | 0 | 1 | 0.498 |
| Specialization | 0.293 | 0 | 0 | 1 | 0.455 |
| University | 0.141 | 0 | 0 | 1 | 0.348 |
| Occupancy | 0.713 | 0.709 | 0.495 | 0.897 | 0.076 |
| 2009_2010 | 0.411 | 0 | 0 | 1 | 0.492 |
| 2009_2010 × University | 0.057 | 0 | 0 | 1 | 0.231 |
| 2009_2010 × Nonprofit | 0.221 | 0 | 0 | 1 | 0.415 |

the fiscal crisis, or whether user charges made up for the shortage of finances.

Additionally, we test whether nonprofit and university hospitals behave differently in years 2009 and 2010. In two robustness checks we include the interaction of the dummy for 2009_2010 and nonprofit status (*2009_2010 × nonprofit*); and 2009_2010 and university status (*2009_2010 × university*). Descriptive statistics of all variables is provided in Table 2.

## 4 Empirical results

In this section, we present and discuss the empirical results of the analysis of Czech hospitals. We perform unconditional and conditional order-*m* analyses. In the 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 environments. Therefore, conditional analysis reveals whether an environmental characteristic has a positive or a negative effect on efficiency.

We analyze the pooled dataset, i.e. a single frontier is constructed and hospitals are simultaneously compared among one another and across time. To check the poolability of the panel (to test whether the frontier is stable over time), we carry out preliminary unconditional efficiency analyses for each year and for a pooled dataset, and compute the Spearman's rank correlation coefficient between single year scores and the scores from the pooled dataset. Correlations vary from 0.87 in 2007 to 0.73 in 2010 and reveal a considerable time stability except for the years 2009 and 2010 (coefficients 0.76 and 0.73, respectively), which will be accounted for in the analysis.

Every non-parametric efficiency analysis is highly sensitive to outliers. Holding $m = 100$ to obtain the order-$m$ scores, each observation out of 389 is compared to a random set of 100 observations.[15] The excessively large efficiency value above 1 would suggest that an observation lies far above the frontier, hence may be an outlier. As Table 3 shows, we do not detect any significant outliers in the sample (the maximum efficiency score is 1.32 and 1.04 in unconditional and conditional analysis, respectively).

Firstly, we present the results of the conditional analysis controlling for several environmental variables which may be beyond the scope of hospital management. Hence, even when they are not direct outputs of a hospital, they affect the way costs are transformed to outputs and should be taken into account. To uncover whether the variables have significant effect upon efficiency, we perform a non-parametric significance test. The direction of influence is retrieved from partial regression plots (see Figs 2 and 3 in the Appendix, plots for other model specifications are available upon request from the authors).

We estimate several specifications: (1) In the top panel, all specifications of Table 4 include all outputs (acute patients weighted by the DRG index, nursing patients, nurse/bed ratio and publications), while the bottom panel serves as a robustness check when a publication output is dropped. Effects of variables are robust across the two panels.

We found that public nonprofit hospitals tend to be less efficient than the for-profit ones, consistent with Dormont and Milcent (2012) or Czypionka et al. (2014). However others (Choi et al. 2017; Zuckerman et al. 1994;

[15] The optimal value of $m$ was set when the percentage of points lying above the frontier stabilized.

**Table 3** Summary of efficiency scores

| | Whole sample | | Small and medium | | Big | |
|---|---|---|---|---|---|---|
| | $\theta(x, y)$ | $\theta(x, y\|z)$ | $\theta(x, y)$ | $\theta(x, y\|z)$ | $\theta(x, y)$ | $\theta(x, y\|z)$ |
| Mean | 0.933 | 0.939 | 0.922 | 0.925 | 0.955 | 0.970 |
| Median | 1.000 | 1.000 | 0.987 | 1.000 | 1.000 | 1.000 |
| Min | 0.408 | 0.391 | 0.408 | 0.391 | 0.544 | 0.673 |
| Max | 1.323 | 1.043 | 1.323 | 1.043 | 1.101 | 1.006 |
| St.dev. | 0.151 | 0.110 | 0.168 | 0.123 | 0.101 | 0.063 |
| Efficiency ≥ 1 | 211 | 210 | 130 | 126 | 81 | 84 |
| Efficiency ≥ 1.1 | 24 | 0 | 23 | 0 | 1 | 0 |
| No. obs | 389 | 389 | 266 | 266 | 123 | 123 |

One benchmark for the whole sample and also for the size groups. Efficiency scores may be >1 as given by the definition of the order-m Free Disposable Hull

**Table 4** Effects of environmental variables: whole sample

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | *P*-value | +/− | *P*-value | +/− | *P*-value | +/− |
| Publications output | | | | | | |
| Nonprofit | 0.052* | − | 0.012** | − | 0.040** | − |
| Specialization | 0.066* | − | 0.016** | − | 0.028** | − |
| University | 0.034** | − | 0.108† | − | 0.018** | *NA* |
| 2009_2010 | 0.110† | − | 0.048** | − | 0.062* | − |
| Occupancy | 0.046** | + | 0.034** | + | 0.284 | + |
| 2009_2010 × Nonprofit | | | <2e-16*** | − | <2e-16*** | − |
| 2009_2010 × University | | | 0.262 | − | | |
| No publications output | | | | | | |
| Nonprofit | 0.026** | − | 0.010*** | − | 0.014** | − |
| Specialization | 0.096* | − | 0.056* | − | 0.056* | − |
| University | 0.078* | *NA* | 0.090* | *NA* | 0.064* | − |
| 2009_2010 | 0.082* | − | 0.126† | − | 0.094* | − |
| Occupancy | 0.024** | + | 0.016* | + | 0.002*** | + |
| 2009_2010 × Nonprofit | | | <2e-16*** | − | 0.004*** | − |
| 2009_2010 × University | | | 0.778 | *NA* | | |

*N* = 389. Effects of the, respective, variables evaluated when all other exogenous variables are kept at the median

*0.1

**0.05

***0.01

†one-tail

*NA* denotes an effect that is hardly recognizable at the median, +/− denotes the favorable/detrimental effect of an environmental variable upon efficiency; bandwidths used to smooth the kernel function are available upon request

Rosko and Chilingerian 1999; Rosko 2001; Herr 2007; Daidone and D'Amico 2009) came to the opposite conclusion. International comparison of the effect of ownership structure on efficiency has to consider differences in the financing structure and institutional characteristics.

Regardless of ownership and legal form, all Czech hospitals are financed primarily through reimbursements from health insurance funds. Besides this, government subsidies may be provided to both nonprofit and corporatized hospitals based on the regional authority's obligation to guarantee accessibility of care in the area. Thus, the lower efficiency of nonprofit hospitals is explained by their different management structure. The result is consistent with Tiemann and Schreyögg (2012) who found that that the corporatization of German hospitals increased efficiency, even though temporarily, whereas privatization was associated with permanent increase in efficiency. The results show that the corporatization which started in 2003 was the right way to increase efficiency of regional nonprofit hospitals. Whether the effect is permanent or only temporary is subject to further research.

We observe hospitals with specialized centers to be less efficient than other units, consistent with Daidone and D'Amico (2009). Hospitals with specialized centers treat more complicated cases (average DRG index is 1.41 compared to 0.87 in non-specialized hospitals) and are more involved in research activities (average publication output 1.59 compared to 0.02). Having controlled for publications and case-mix among outputs, the fact that specialization dummy is significant suggests that the DRG case-mix index does not reflect the severity of cases properly. Indeed, the Czech DRG system was introduced as a payment mechanism in 2007 and was abandoned shortly after due to a number of drawbacks. Currently, there is a new initiative called "DRG Restart", the goal of which is to implement a new functioning DRG system until 2020. Even though not optimal, however, the DRG case mix index still decreases variation across efficiency scores of Czech hospitals when results with and without case-mix adjustment are compared.

Despite the fact that university hospitals are more involved in research reporting more publications (publication output 3.03 on average compared to 0.06 for non-university hospitals), which represents their comparative advantage relative to other hospitals in the sample, they are found to be less efficient than other hospitals. A different structure of services (more costly treatments), and management and organization of resources drive their efficiency down. Hence, even the introduction of publication output is not sufficient to make university hospitals comparable to other hospitals. The result is consistent with Rosko (2001), Grosskopf et al. (2001a) or Choi et al. (2017).

Our results thus suggest that there may be other factors specific to university hospitals and specialized centers which drive their efficiency down (e.g. they run costly research experiments, doctors' salaries may be extremely high, number of doctors may be relatively large, quality of treatment is not properly measured).

The joint dummy variable for years 2009 and 2010 reflects the introduction of user charges for each inpatient day which increased hospitals' revenues on one hand, and potential fiscal stress due to the financial crisis on the other hand. The results indicate that hospitals were not under fiscal stress that would force them to undertake restrictive measures, as the efficiency of hospitals is lower in years 2009 and 2010. Additional revenues from user charges seem to influence costs, but do not translate to outputs of our analysis. We, however, cannot say that hospitals waste more money, as these financial resources may contribute to outputs not measured in our analysis.

Occupancy rate reflects the utilization of potential capacity in a hospital. In the short term, the number of beds is given and a hospital has fixed costs related to its capacity; if the number of patients is far below a hospital's capacity, the hospital is expected to be less efficient as proved for an occupancy rate below 0.7. For rates above 0.7, the effect is not clear anymore (see the partial regression plot in Fig. 2 in the Appendix) suggesting that hospitals may target below its potential capacity to accommodate fluctuations in emergency admissions (Jacobs and Dawson 2003).[16]

In models (2) and model (3), we additionally test for the specific behavior of university and nonprofit hospitals in years 2009 and 2010. On one hand, we do not find any significant effect for university hospitals. On the other hand, the effect for nonprofit hospitals is significantly negative. Hence, the efficiency of nonprofit hospitals decreases in years 2009 and 2010 even more relative to other hospitals.

Table 3 provides summary statistics of efficiency scores for the conditional efficiency model ($\theta(x, y|z)$) and unconditional model ($\theta(x, y)$).[17] The mean of both unconditional and conditional efficiencies of the whole sample is considerably high, reaching 0.933 and 0.939, respectively. Hence, a hospital can save on average 6.7% of its costs. Constrained by the operating environment, an average hospital can save only around 6.1%.

Conditional efficiency analysis controls for other aspects affecting the production process and increases/decreases efficiency of a unit operating in detrimental/favorable environment, thus the standard deviation of efficiency scores for the conditional model naturally decreases.

We disaggregate the sample of hospitals according to size to uncover different patterns of efficiency for small and medium, and big hospitals; big hospitals treat more than

[16] The paper presents only the final models which have the best fit. We also tested the effect of the number of beds, however, it was not significant. Moreover, the number of beds is highly correlated with the number of patients adjusted for DRG (correlation 0.94). We then tested the effect of cost conditions (average gross salary) on hospitals' efficiency, but no significant result was found either. All the tested specifications are available upon request.

[17] Efficiency scores for alternative specifications of the conditional model (1), (2) and (3) are very similar (Spearman's correlation coefficients vary from 0.97 to 0.988 (and are around 0.864) within (across) models with and without publications), hence we present summary of scores only from the preferred model (3) with the publication output.

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

| | Full list of outputs | | | | No publication output | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (1) | | (2) | |
| | *P*-value | +/− | *P*-value | +/− | *P*-value | +/− | *P*-value | +/− |
| Small and medium hospitals, $N = 266$ | | | | | | | | |
| Nonprofit | 0.034** | – | 0.016** | – | 0.052* | – | <2e-16*** | – |
| Specialization | 0.072* | – | 0.054* | – | 0.022** | – | 0.038** | – |
| Occupancy rate | 0.068* | + | 0.038** | + | 0.030** | + | 0.070* | + |
| 2009_2010 | 0.358 | *NA* | 0.248 | – | 0.112† | – | 0.062* | – |
| 2009_2010 × Nonprofit | | | 0.108† | – | | | <2e-16*** | – |
| Big hospitals $N = 123$ | | | | | | | | |
| Nonprofit | 0.052* | + | 0.106† | + | 0.344 | + | 0.320 | + |
| Specialization | 0.360 | – | 0.470 | + | 0.082* | – | 0.090* | – |
| 2009_2010 | 0.862 | – | 0.632 | – | 0.730 | *NA* | 0.572 | – |
| University | 0.060* | + | 0.148† | + | 0.132† | + | 0.196† | + |
| Occupancy rate | 0.006*** | mixed | 0.028** | mixed | 0.196† | mixed | 0.356 | mixed |
| 2009_2010 × Nonprofit | | | 0.878 | – | | | 0.864 | + |
| 2009_2010 × University | | | 0.180† | + | | | 0.796 | + |

Effects of the, respective, variables evaluated when all other exogenous variables are kept at the median

*0.1

**0.05

***0.01

†one-tail

*NA* denotes an effect that is hardly recognizable at the median, +/− denotes favorable/detrimental effect of an environmental variable upon efficiency; bandwidths used to smooth the kernel function are available upon request

20,000 patients a year on average. Unconditional and conditional mean efficiencies are lower for small and medium hospitals, however the efficiency of small and medium hospitals varies a lot. On one hand, there are several small and medium hospitals with very low scores far below the least efficient big hospital. On the other hand, there are some medium and small hospitals with higher efficiency than the most efficient big hospital. When moving from unconditional to conditional analysis, we can observe much larger improvements in scores for big hospitals than for other units. It is because big hospitals are often nonprofit university hospitals with specialized centers and all these factors were found to be detrimental to efficiency.

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

Concerning small and medium hospitals, effects in Table 5 are consistent with the aggregate results. The only difference is the insignificance of the joint year dummy for the specification with the full list of outputs, but it becomes significant when publication output is dropped. Hence, when small and medium hospitals are considered, additional revenues from user charges in 2009 and 2010 could have been spent on research activity, as the production of publication for some of these hospitals increased (average publication output increased from 0.033 to 0.056 between periods 2006–2008 and 2009–2010). Nevertheless, nonprofit small and medium hospitals seem to increase their spending without increasing outputs measured in this analysis as they become more inefficient in 2009 and 2010.

Results for big hospitals show a slightly different pattern. Contrary to the aggregate analysis, nonprofit and university hospitals tend to be more efficient within the group of big hospitals, although the effects are very weak and not significant for all specifications (under a stricter confidence level, the effect would be insignificant). It seems that these hospitals tend to have more publications (effects are more significant when publication output is included in the analysis) than other big hospitals (for example, university hospitals have publication output on average around 3.05, while other big hospitals' average is around 0.28).

We cannot observe a significant effect of specialized centers when publications are considered among outputs. But hospitals with specialized centers become less efficient when publications are dropped from the list of outputs, i.e. research activity is a relevant output requiring additional costs in these hospitals. Surprisingly, we do not find any significant effect of joint year dummy 2009 and 2010. Hence, it seems that two contradictory pressures (increase in revenues due to introduction of user charges and fiscal stress in the financial crisis) balance resulting in no specific effect. A weak effect upon efficiency can only be observed for university hospitals, revealing some minimal cost-saving measures when university hospitals are compared to other big hospitals.

## 5 Conclusion

This paper analyzed the cost efficiency of 81 hospitals in the Czech Republic during the period 2006–2010. We assessed how the operating costs, the only input in the analysis, translated to the following outputs: acute care patients adjusted for the DRG-case-mix index, nursing patients, the nurse/bed ratio, and publications reflecting research activity of a hospital.

We employed the non-parametric conditional order-*m* analysis. The conditional order-*m* approach overcomes drawbacks of the one-stage and two-stage approaches, namely separability conditions, parametric assumptions, assumptions of free disposability or convexity of the attainable set, all of which are quite restrictive (for more discussion see Bădin et al. 2014).

Regarding environmental variables, we controlled for nonprofit status, the presence of a specialized center in a hospital, teaching status, and occupancy rate. We also tested whether efficiency increased or decreased in the years 2009 and 2010, when there was an important legislative change giving hospitals additional revenues through user charges. This period was, however, marked also by the financial crisis putting hospitals under fiscal stress. Additionally we include interaction terms that control for the effect financial pressures may have on nonprofit and teaching hospitals.

To uncover whether effects of environmental variables were specific to the 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.

The mean of both unconditional and conditional efficiencies of the whole sample is considerably high, reaching around 0.935. Hence, a hospital can save on average around 6.5% of its costs. We observed that the differences of efficiency scores within the group of big hospitals are much lower than in the other group.

We found that the nonprofit hospitals tend to be less efficient than their for-profit counterparts due to a different management structure. This finding contributes to the current political discussions concerning the restructuring of nonprofit hospitals. We also uncovered that hospitals with specialized centers tend to be less efficient. There are two explanations at stake: (i) DRG case-mix index does not reflect the severity of treatments properly, and (ii) there are other specific factors which reduce efficiency of these hospitals (e.g. costly experiments, many doctors, high salaries of leading professionals in the field).

University hospitals were found to be comparatively less efficient. The complexity of cases and management structure reduces their efficiency even when controlling for publication output, which is much larger for university hospitals than in other units. However, university hospitals are more efficient relative to the sample of big hospitals.

Concerning the effect of years 2009 and 2010, we did not find that hospitals were under fiscal stress and were forced to save. On the contrary, due to the introduction of user charges, revenues and spending increased, but outputs did not increase equivalently, making hospitals less efficient in this period. Potential waste of this additional financial resources was even more alarming in nonprofit hospitals. Within the group of big hospitals, however, university hospitals were found to become more efficient in this period.

There are several lessons for policy-makers arising from this analysis: (i) Czech hospitals form a rather heterogenous group and when assessing their efficiency, big hospitals should be treated separately from other hospitals as their efficiency follows a different pattern; (ii) the structure of management in nonprofit hospitals reduces their efficiency; (iii) hospitals with specialized centers and university hospitals have specific characteristics which generally deter their efficiency and hence deserve special attention.

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### Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

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## 6 Appendix

Figures 2 and 3.

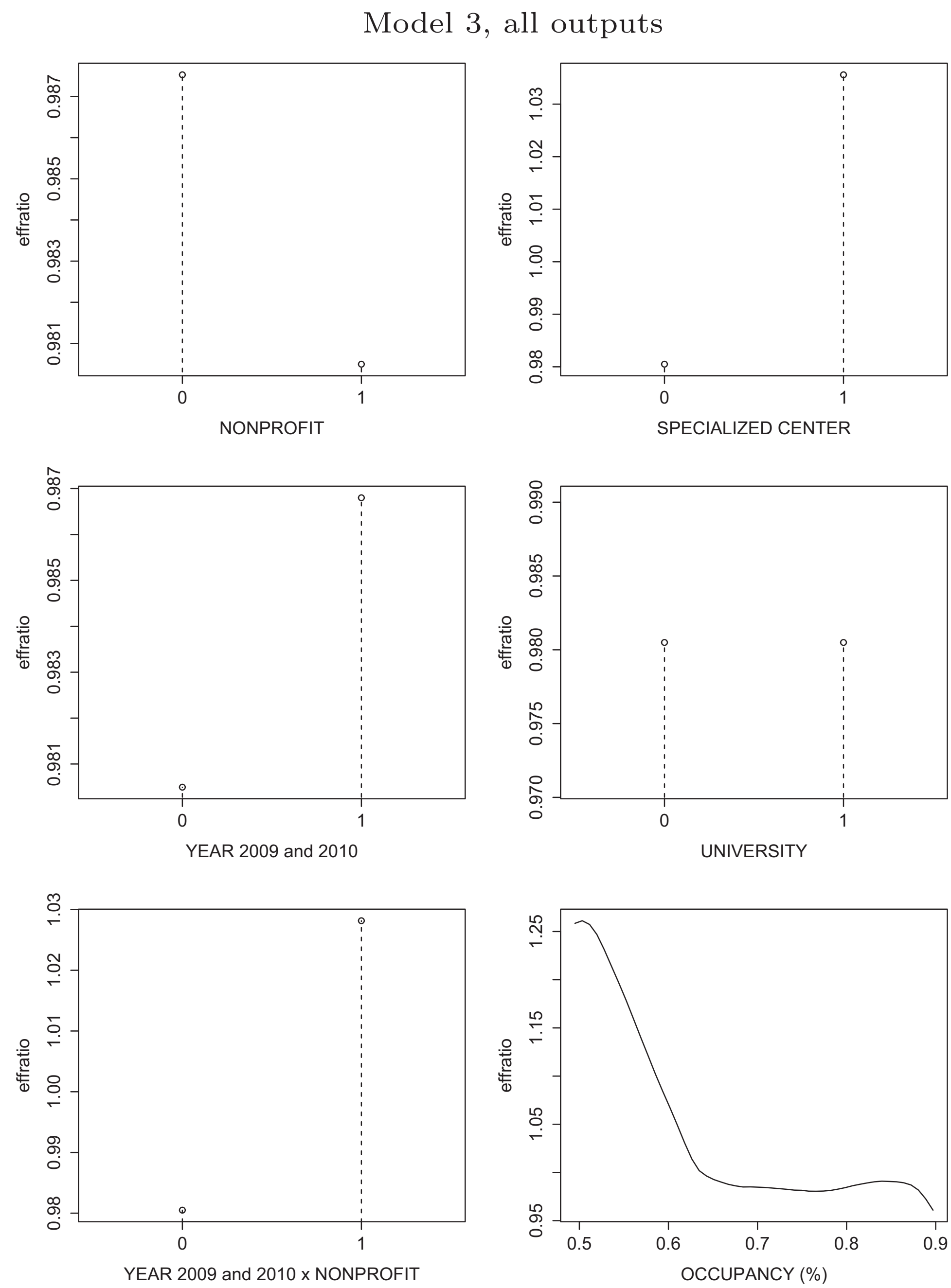



**Fig. 2** Partial regression plots: whole sample

**Fig. 3** Partial regression plots: small and medium vs. big hospitals

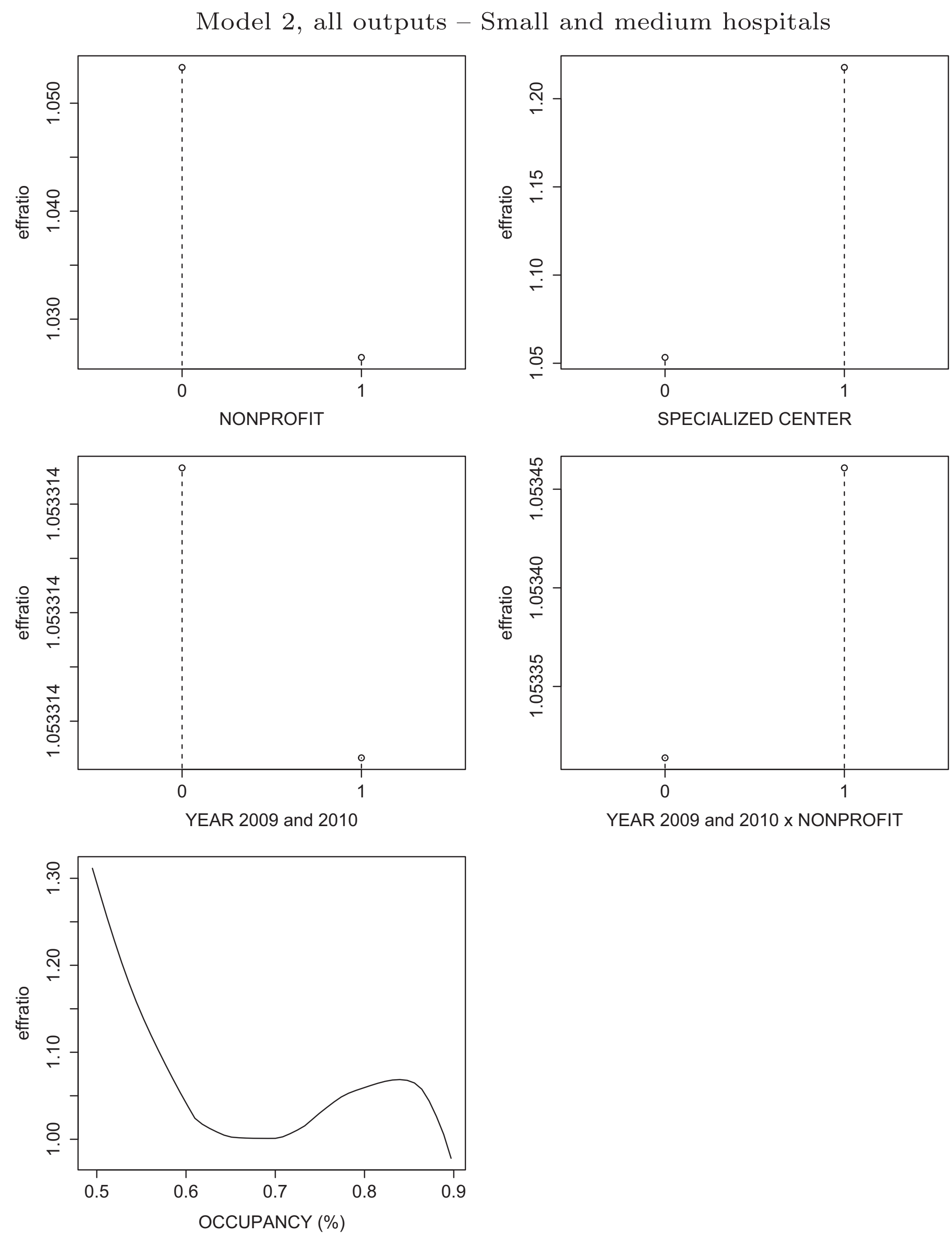
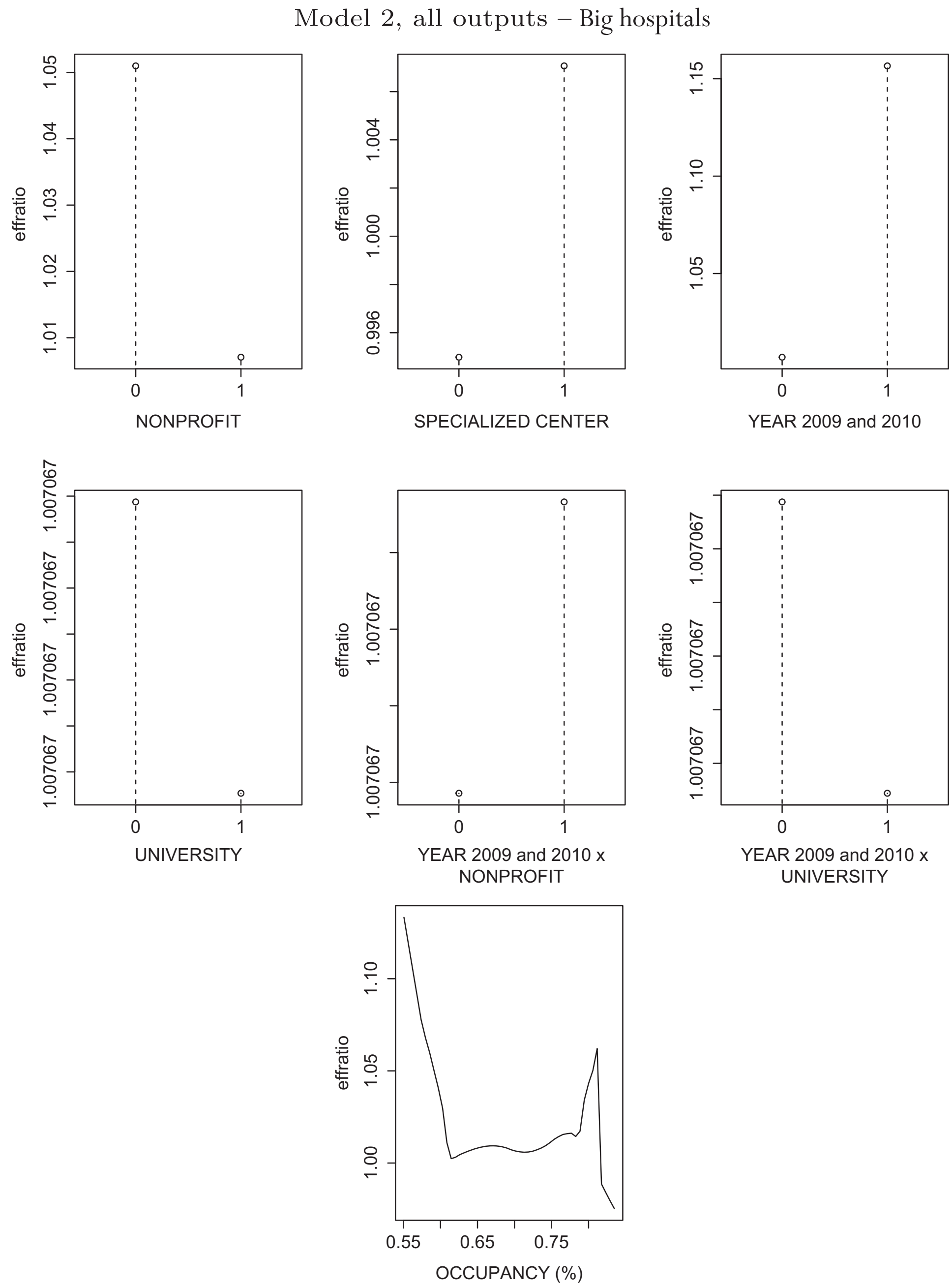


**Fig. 3** (Continued)

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