Tiemann, Oliver; Schreyögg, Jonas

**Working Paper**

# Changes in hospital efficiency after privatization

hche Research Paper, Hamburg Center for Health Economics, No. 2011/02

**Provided in Cooperation with:**
Hamburg Center for Health Economics (hche), University of Hamburg

Universität Hamburg

Hamburg Center
for Health Economics

## Changes in Hospital Efficiency after Privatization

Oliver Tiemann and Jonas Schreyögg

Research Paper

2011/02

Changes in Hospital Efficiency after Privatization
Oliver Tiemann and Jonas Schreyögg

## Abstract

We investigated the effects of privatization on hospital efficiency in Germany. To do so, we obtained bootstrapped DEA efficiency scores in the first stage of our analysis and subsequently employed a difference-in-difference matching approach within a panel regression framework. Our findings show that conversions from public to private for-profit status were associated with an increase in efficiency of between 3.2 and 5.4%. We defined four alternative post-privatization periods and found that the increase in efficiency after a conversion to private for-profit status appeared to be permanent. We also observed an increase in efficiency one year after hospitals were converted to private non-profit status, but our estimations suggest that this effect was transitory. Our findings also show that the efficiency gains after a conversion to private for-profit status were achieved through substantial decreases in staffing ratios in all analyzed staff categories with the exception of physicians. It was also striking that the efficiency gains of hospitals converted to for-profit status were significantly lower in the DRG era than in the pre-DRG era. Altogether, our results suggest that converting hospitals to private for-profit status may be an effective way to ensure the scarce resources in the hospital sector are used more efficiently.

*Oliver Tiemann*
*Universität Hamburg*
*Fakultät WISO*
*Von-Melle-Park 5*
*20146 Hamburg*
*Germany*
*oliver.tiemann@wiso.uni-hamburg.de*

*Jonas Schreyögg*
*Universität Hamburg*
*Fakultät WISO*
*Von-Melle-Park 5*
*20146 Hamburg*
*Germany*
*jonas.schreyögg@wiso.uni-hamburg.de*

**1. Introduction**

Rising health expenditure and tight public budgets over the past four decades have led decision makers in many Western industrialized countries to seek ways to improve the performance of health care organizations. Hospitals, in particular, are increasingly being held accountable for their efficiency and financial performance. Having identified inefficiencies and financial risks in public hospitals, national and local governments in a wide range of countries have responded by privatizing these institutions. The chief motivation behind the privatizations that have taken place in these countries during the past twenty years has been the expectation that shifting from public to private ownership would lead to gains in organizational performance, especially in terms of efficiency.

Considering the importance of this topic, not least in the political debate, the lack of quantitative empirical studies on the effects of hospital privatization is surprising, as is the small number of studies analyzing the effects of conversions in hospital ownership in general. The present investigation is the first to examine the effects of privatization on technical efficiency in the hospital market. To do so, we examined a large sample of German hospitals that changed from public to either private non-profit or to private for-profit status.

Following an extensive wave of privatizations that began in the mid-1990s, the large hospital market in Germany is now fertile ground for investigating these effects. In Germany, three different types of hospital ownership have co-existed for decades: private for-profit, private non-profit, and public. As their classification implies, both types of private hospitals are owned by private entities, whereas public hospitals are owned mainly by public entities, such as local or

regional governments. Between 1995 and 2008, a substantial number of local and regional governments in Germany sold their hospitals to private for-profit and private non-profit owners. The total number of private for-profit hospitals increased by 164, or 44%, which represented a rise in market share from 6 to 18% measured in terms of hospital beds. During the same period, the market share of private non-profit hospitals decreased slightly, from 38 to 36%, because some private non-profit hospitals were also converted to private for-profit ownership (Federal Statistical Office of Germany, 2009).

In the present study, we focused on technical efficiency to assess changes in hospital performance following privatization. After using a bootstrapped data envelopment analysis (DEA) technique to estimate efficiency scores for each hospital in our sample, we employed propensity score matching to ensure that the two groups of hospitals in our analysis (i.e. privatized and non-privatized) were comparable in terms of organizational characteristics, environmental characteristics, and patient heterogeneity. Subsequently, following an approach suggested by Simar and Wilson (2007), we estimated a second-step regression model for truncated longitudinal data, with bootstrapped DEA efficiency scores as dependent variable. Finally, while controlling for the impact of hospital organizational and environmental characteristics, we applied a difference-in-difference specification of the regression model to examine whether privatization improved hospital efficiency.

The second section of this paper reviews the relevant theoretical and empirical literature on privatization and its impact on organizational performance. The third section presents the setting, data, and methodology used to explore this relationship. The fourth section describes and

discusses the results of our analysis, and the fifth, and final, section draws conclusions and suggests topics for future research.

## 2. Previous literature on privatization

Most of the existing research on privatization relies on agency theory, property rights theory, or public choice theory, each of which provides different explanations of a common outcome. According to all three theories, the rationale for privatization is that the resulting changes in an organization's objectives, incentives, and control mechanisms lead to improved performance: Public hospitals acquired by a private for-profit organization are expected to maximize profit through a high degree of technical efficiency, producing services in such a way that marginal cost will equal marginal revenue. In turn, public hospitals acquired by a private non-profit organization are expected to improve technical efficiency by suppressing politically motivated resource allocation and expanding their output at least to the point where total cost equals total revenue (Haskel and Szymanski, 1993; Shleifer and Vishny, 1994; Bös, 1991; Boycko *et al.*, 1996; Laffont and Tirole, 1993; Sappington, 1987; Schmidt, 1996; Vickers and Yarrow, 1991).

Generally speaking, there have been – from an empirical point of view – two categories of studies that deal with ownership and privatization. The first, and by far the most numerous, of these have compared the performance of public and private entities in industries in which both types of ownership coexist (Villalonga, 2000). In a meta-review of studies of this nature that focused on the hospital market, Shen *et al.* 2007 concluded that there was little evidence supporting the standard assumption that private for-profit hospitals outperform hospitals with other types of ownership. Herr (2008) and Tiemann and Schreyögg (2009) found that public hospitals

3

outperform hospitals with other types of ownership in the German hospital market. Because none of these studies investigated changes in ownership type during a specified period – and thus did not examine the effects of privatizing public entities – they will not be discussed in any further detail below.

The second category of studies has focused on privatization and its impact on organizational performance, usually employing a longitudinal design. From a methodological perspective, these studies have taken two different approaches. The first was introduced by Megginson *et al.* (1994), who compared the means and medians of the periods before and after privatization according to defined performance criteria. Few of the studies that have taken this approach, however, have included control groups consisting of non-privatized state-owned organizations. The second approach has involved much larger samples of privatized entities and, defining the privatization event as an intervention, has applied methods proposed in the literature on program evaluation (Heckman and Hotz, 1989; Heckman *et al.*, 1997). The majority of these studies have used some kind of difference-in-difference method to analyze the effects of privatization on performance compared to the performance of a control group of non-privatized entities, controlling for time-invariant differences between the groups. As part of our literature review, we were able to identify ten studies from different industries that used such a method to evaluate privatization effects, including four studies on hospitals: Picone *et al.* (2002), Shen (2002), Shen (2003) and Farsi (2004), all of whom examined ownership conversion effects in the US hospital market.

Three of these four studies assessed the quality of care after a change in ownership and found that conversions from private non-profit to private for-profit status had a significantly negative impact

4

(Picone *et al.*, 2002; Shen, 2002; Farsi, 2004). One study (Farsi, 2004) found that a change from private for-profit to private non-profit status also had a negative effect on the quality of care.

Using profit margins, capacity, staffing ratios, salaries, patient mix, and the amount of unprofitable care as measures, Shen (2003) and Picone *et al.* (2002) examined the impact of changes in ownership on hospital performance. Both studies found that hospitals converted from public or private non-profit status to private for-profit status increased their profit margins and reduced staffing ratios. In addition, Shen (2003) found that these hospitals reduced cost and increased revenue. She also found that a change from public or private for-profit status to private non-profit status resulted in slight reductions in cost and in nursing staff, but did not lead to increased profit margins.

Although all four studies were pioneering in their approach and focus, they have several important weaknesses. First, Shen (2003) and Picone *et al.* (2002) used profit margins as a measure of performance. There is evidence, however, that public hospitals are averse to seeking profit maximization (Pestieau, 2009). As a result, it seems reasonable to assume that using financial performance criteria, such as profit margins, may lead to bias in pre-post comparisons of privatized entities and control group designs. For this reason, we believe that productivity, in terms of technical efficiency, is a more suitable measure of changes in performance among hospitals that have undergone a conversion in ownership type. Second, none of the four studies specifically examined the phenomenon of privatization, which would have required a focus solely on changes from public status to private non-profit or private for-profit status. Instead, they examined the effects of conversion from any form of ownership to public, private non-profit, or private for-profit status. Third, Shen (2002 and 2003) was the only author to address the problem

of causal interference, using a difference-in-difference method combined with a matching approach to investigate the impact of privatization. Finally, all four studies implicitly assumed that changes in performance are attributable primarily to changes in ownership status. There may, however, be other changes to the market environment, such as the introduction of diagnosis-related groups (DRGs), that also interact with the privatization event.

By focusing on the impact of privatization on technical efficiency and employing a difference-in-difference matching approach, we attempt to address these shortcomings and contribute to the current understanding of the consequences of hospital privatization.

## 3. Research design and methods
### 3.1 Data envelopment analysis

In the hospital sector, DEA is the most frequently used approach to measuring efficiency (Hollingsworth, 2008). A linear programming technique for evaluating the relative technical efficiency of individual organizations based on observed data, DEA defines the relative efficiency of an organization as the ratio of the weighted sum of its outputs to the weighted sum of its inputs. The weights are not pre-assigned, but rather determined by the model, thus avoiding any bias resulting from subjectively assigned weights. DEA allows multiple inputs and outputs to be considered simultaneously, which seems particularly well-suited to measuring the efficiency of complex service organizations like hospitals. In contrast to parametric methods such as stochastic frontier analysis (SFA), DEA has the advantage of not requiring that any assumptions be made about the functional form of the production or cost frontier. This reduces the need for a theoretical exposition of the model. SFA is also frequently used to measure efficiency in health

care organizations. Because both techniques have their strengths and weaknesses, Coelli *et al.* (1999) propose evaluating their suitability depending on the context of study. As in other investigations that have measured hospital efficiency, our decision to use DEA was driven by data availability (Pilyavsky *et al.*, 2006): our data set contained a range of input and output variables suitable for DEA, but did not contain input prices, which are an important prerequisite for SFA.

Based on our understanding of the market constraints within the German hospital sector, we assumed variable returns to scale, which may be appropriate when it is impossible to assume that all observed units are operating at an optimal scale (Banker *et al.*, 1984). In the health care sector, imperfect competition and budgetary constraints, as well as regulatory constraints on entry, mergers, and exits, can often cause organizations to operate at an inefficient scale size (Jacobs *et al.*, 2006). In light of this theoretical framework, we used the following empirical model in our analysis. In the input-oriented case, we estimated the variable returns to scale model by Banker, Charnes, and Cooper (BCC) as a linear programming problem, as follows (Banker *et al.*, 1984):

$\vartheta_i$, $i = 1, \dots, n$ is the hospital's efficiency, where $n$ represents the number of observations (i.e. the number of hospitals).

$\vartheta_i = 1/\theta_i$, where $\theta_i$ is the inefficiency.

Matrix $\mathbf{X} \in \mathbb{R}^{k \times n}$ refers to $k$ observed inputs of $n$ compared hospitals, and matrix $\mathbf{Y} \in \mathbb{R}^{r \times n}$ refers to $r$ observed outputs of the compared hospitals. Vectors $\mathbf{x}_i \in \mathbb{R}^k$ and $\mathbf{y}_i \in \mathbb{R}^r$ represent the

inputs and outputs of unit $i$ (i.e. the $i$th columns of matrix $\mathbf{X}$ and $\mathbf{Y}$, respectively). Furthermore, $\mathbf{1}$ refers to a column vector of ones with a suitable dimension. The DEA efficiency score, which is the reciprocal of the inefficiency $\theta_i$, can be obtained by solving the following BCC linear programming model (Syrjänen, 2004):

(1) $\qquad \theta^* = Min\theta,$

(2) s.t. $\quad \mathbf{Y}\boldsymbol{\lambda} - \mathbf{y}_0 \geq \mathbf{0},$

(3) $\qquad -\mathbf{X}\boldsymbol{\lambda} + \theta\mathbf{x}_0 \geq \mathbf{0},$

(4) $\qquad \mathbf{1}^T\boldsymbol{\lambda} = 1, \ \boldsymbol{\lambda} \geq \mathbf{0}.$

Using DEA efficiency scores for a second-stage regression has been found to result in inconsistent estimates unless these scores are corrected by a bootstrapping procedure. The procedure applied in the present study follows the approach developed by Simar and Wilson (1998, 2000). In our case, the bias-corrected scores were derived from 500 bootstrap iterations, which allowed us to estimate a robust regression model for the second-stage analysis (see Section 3.3).

## 3.2 Propensity score matching

The difference-in-difference estimator has the advantage of eliminating unobserved time-invariant hospital-level effects between privatized and non-privatized hospitals. It does not, however, address the problem of potential baseline imbalance between these two groups, which can be caused when large differences in group characteristics prior to privatization lead to selection bias. In the case of baseline imbalance, results may be very sensitive to the model specification, and regression analysis may effectively extrapolate outside the support of the data. Methods such as propensity score matching have been shown to avoid unreliable inference in

parametric models. Whereas the use of matching estimators alone is usually unsatisfactory due to the strong assumption that selection is based only on observables, several authors have proposed that a combination of difference-in-difference and propensity score matching methods significantly increases the quality of non-experimental evaluation results (Blundell and Dias, 2000; Smith and Todd, 2005).

We thus applied a propensity score matching approach proposed by Rosenbaum (2002) and Rubin (1973, 2006) and extracted a sub-sample of non-privatized hospitals in which the distribution of covariates was similar to that in our sample of privatized hospitals. In the first step, we estimated the conditional probability that any hospital in the two samples had been privatized during the study period given the vector of our defined covariates. The propensity scores were derived by performing a logistic regression. In order to achieve a propensity score model that minimizes the conditional bias, it is important to determine predictors and confounders of the intervention–outcome relationship and to identify predictors of exposure (Austin, 2008). To determine appropriate predictors of exposure, we tested different models, allowing for interactions between variables (for a detailed description of the variables, see Section 4.2). Subsequently, we calculated the predicted probabilities of belonging to the sample of privatized hospitals. Based on this score, each privatized hospital was matched to one non-privatized hospital in the corresponding baseline year (i.e. one year before the privatization occurred). Because the propensity score was the only pre-intervention measurement, the matching algorithm minimized the absolute differences in propensity score (Rosenbaum, 1989). By using one-to-one matching with replacement, the total distance between matched pairs was also minimized; known as optimal matching, this method ensures that conditional bias is reduced to a minimum (Rosenbaum, 2002; Rubin, 2006; Schreyögg *et al.*, 2010). The number of pairs in

the matched sample was further restricted by using calipers of width equal to 0.2 of the standard deviation. A comparison of different caliper widths found that this width was superior to others at reducing conditional bias in the estimation of intervention effects (Austin, 2009).

We assessed the appropriateness of our propensity score matching by using standardized differences for continuous variables and differences for non-continuous variables as recommended by Austin (2008). Standardized differences represent a good measure of appropriateness for the matching procedure, as they depend neither on the unit of measurement nor on the size of the sample (Imai *et al.*, 2008). Furthermore, we applied Hotelling's T-square statistic to test the reliability of our propensity score matching. Whereas standardized differences and differences rely on the cross-sample difference of each variable included in the propensity score matching model, Hotelling's T-square test considers whether these differences can be taken as jointly insignificant. In the present study, we divided the sample by propensity score quartiles and conducted the test for each sub-sample (Girma and Görg, 2007).

### 3.3 Difference-in-difference estimates

In our regression analysis, we applied a linear regression model for truncated longitudinal data with DEA efficiency scores as dependent variable. A difference-in-difference specification of the regression model was used to assess whether privatization led to improvements in efficiency while controlling for patient heterogeneity and the impact of hospital organizational and environmental characteristics. Truncated regression models were chosen owing to the truncated distribution of the DEA-based relative efficiency estimates (Simar and Wilson, 2007). All of our difference-in-difference regressions were modeled with fixed effects and random effects because

10

the results of the Breusch–Pagan and Hausman tests suggested that the assumption of the random effects specification was also appropriate. Although we reported both the fixed effects and the random effects regression results, the fixed effects estimator generally provides more consistent estimates and may pick up much of the unobserved heterogeneity in the hospital-specific effect. Because of this, the fixed effects estimator was our preferred model. Our model was a follows:

$$(5) \qquad \vartheta_{it} = \beta_0 + \beta_1 PRIV_i + \beta_2 POST_{it} + \beta_3 PRIV_i POST_{it} + \beta_4 Z_{it} + \varepsilon_{it}$$

where $\vartheta_{it}$ is the efficiency of the $i$th hospital at year $t, t = 1, \ldots, 13$; $PRIV_i$ is a dummy variable for privatization, with $PRIV_i$ being assigned a value of 1 if a hospital was privatized at any time between 1997 and 2007 and a value of 0 if not; $POST_t$ is assigned a value of 1 in the years after privatization and 0 before the year during which the hospital changed its status to private for-profit or private non-profit; and $Z_{it}$ are observable factors affecting the efficiency of hospital $i$ at year $t$ (i.e. hospital characteristics, environmental characteristics, and patient heterogeneity; a detailed description of the variables is provided in Section 4.2). The random term $\varepsilon_{it}$ is assumed to be normally distributed with zero mean.

The variable $PRIV_i$ was included to control for time-invariant differences between privatized hospitals in the intervention group (i.e. hospitals that were converted from public to private for-profit or private non-profit status) and non-privatized hospitals in the control group. The coefficient of interest is the interaction between $PRIV_i$ and $POST_t$, which identifies changes in efficiency after a hospital was privatized relative to efficiency in the comparator group. The difference-in-difference methodology assumes that all other temporal factors affecting hospital

11

efficiency had the same impact on hospitals in the intervention group as they did on hospitals in the control group. We thus assume that any changes over time for which we did not control affected all hospitals in the same way. For sensitivity purposes, and to check the robustness of our estimates, we allowed for four alternative post-privatization periods (i.e. first, second, third, and fourth year). The pre-period was defined as the year before privatization occurred and alternatively year 2 before privatization was used.

An important assumption in our study was that environmental and organizational factors can influence the efficiency of hospitals in addition to a change in ownership status. We assert that considering the impact of such covariates on hospital efficiency provides a better explanation of variation in efficiency and more robust findings on the post-acquisition effects of privatization than the approaches taken in previous studies on this topic, none of which controlled for these effects. The use of control variables is of particular importance when examining the hospital market because there are usually a range of structural and regulatory determinants of efficiency that a hospital itself cannot influence. Table 1 provides a comprehensive outline of our statistical analysis.

------------------------------
Insert Table 1 about here
------------------------------

12

## 4. Data

### 4.1 Sample

The data for our study were derived from the annual hospital reports collected and administered by the Research Data Centre of the Statistical Offices of the Länder. This rich dataset covers all public, private for-profit, and private non-profit hospitals in Germany and contains hospital-level information on cost and hospital infrastructure, as well as patient-level information on age, diagnoses, and procedures performed. Our study is based on data from the years 1996 through 2008, and the unit of analysis was the hospital. Due to data privacy issues, we were able to obtain randomly selected data for only two-thirds of German acute care hospitals ($n = 1878$). To ensure the comparability of the hospitals in the sample, the following institutions were excluded from further analysis: hospitals providing only psychiatric care; university hospitals; day clinics; hospitals with fewer than 50 beds or more than 2000 beds; and private non-profit and private for-profit hospitals that had been privatized before the study period. In addition, manual plausibility checks were conducted to identify any measurement errors. Ultimately, a total of 548 public hospitals remained in our sample, including 132 that were privatized between 1997 and 2007. Of these 132 hospitals, 99 were acquired by a private for-profit organization and 33 were acquired by a private non-profit organization (Research Data Centre of the Statistical Offices of the Länder, 2009). Table 2 shows the number of hospital privatizations per year.

------------------------------
Insert Table 2 about here
------------------------------

## 4.2 Description of variables

When selecting inputs and outputs for the first stage of our analysis, we followed the example of other studies that have developed DEA frameworks for measuring hospital efficiency (Pilyavsky *et al.*, 2006; Jacobs *et al.*, 2006; Burgess and Wilson, 1998). For our purposes, we chose six inputs and two outputs. The first input variable (SUPPLIES) represents the amount spent on supplies per year, including operational expenses, but excluding payroll, capital, and depreciation expenses. Taking into account the relative importance of resource use in terms of labor in the hospital production process, we chose the number of full-time equivalents (FTEs) for the following personnel categories as additional input variables: physicians (PHYS), nursing staff (NURSE), other clinical staff (CLIN), administrative staff (ADMIN), and other nonclinical staff members (NONCLIN).

In our first DEA efficiency model, we used the number of inpatient cases per year in each hospital as the only output variable (INPATIENT). A second model specification served as a sensitivity analysis to test whether the efficiency scores and ranks remained stable when a measure of quality of care was employed as a second output. To do so, we used the average in-hospital mortality rate per year for each hospital to adjust for variations in the quality of care between hospitals. The second output thus represents the number 1 minus the average in-hospital mortality rate per year (1-MORTALITY).

Using output variables like these can be problematic if patient heterogeneity (i.e. case mix) varies systematically across the hospitals in a sample. This is because hospitals with a more complex case mix are likely to receive lower efficiency scores. To address this potential shortcoming, we

used patient-level data to condense a comprehensive set of comorbidities to a single numeric score that (a) summarized disease burden and resource use and (b) was sufficiently discriminative for predicting mortality. In order to generate this case-mix index for each hospital, we relied on the comorbidities included in the Elixhauser Comorbidity Index (van Walraven *et al.*, 2009). We used this case-mix index to risk-adjust both of the output variables for the DEA models. Another common approach would have been to use a case-mix index whose weight reflected the relative costliness of DRGs. Carey (2000, 2002), however, reported that individual-level measures represent a vast improvement over such aggregate case-mix measures when controlling for patient heterogeneity.

A correlation analysis showed that our multiple inputs were positively correlated with our output set. This is an important prerequisite for applying DEA. In the present study, the input variables, in particular, were highly correlated, which suggests that a limited number of inputs might have been sufficient to represent the selected input set in our efficiency assessment. Several authors (e.g., Dyson *et al.*, 2001; Jacobs *et al.*, 2006), however, emphasize that correlation is an aggregate measure of the closeness of two sets of observed data and argue that omitting a highly correlated variable can lead to significant changes in efficiency estimates. As a result, variations in the input levels for individual hospitals may have little impact on the correlation while significantly affecting the measured efficiency. A comprehensive set of inputs and outputs may also increase the chance of identifying the presence of a production technology common to all decision-making units. In addition, Dyson *et al.* (2001) argue that omitting variables to increase discrimination is less effective when using large data samples. Based on these considerations, we chose to use all of our input variables for the DEA model. Table 3 shows the descriptive statistics for in- and

outputs of our sample used in the DEA models stratified according to the intervention and control groups.

------------------------------
Insert Table 3 about here
------------------------------

In the second stage of our analysis, heterogeneity in hospital characteristics was covered by several variables. The first of these was the number of licensed and staffed beds (BEDS), an approach taken in previous studies to control for hospital size (Carey *et al.*, 1999; Dudley *et al.*, 2000; Harrison *et al.*, 2004). In the context of hospital planning in Germany, the number of beds per hospital can be seen, at least over the medium term, as an exogenous factor that is not under the direct control of hospital management. To account for higher resource consumption due to differences in teaching activities, we included a variable (TEACHING) for the training activities of non-medical staff. These activities are represented by the ratio of trainee positions and the sum of all non-medical personnel. Another important point to consider is that hospitals may lease facilities to private-practice physicians (e.g. for hospital outpatient surgery). The estimated DEA efficiency scores calculated in the first stage of our analysis were higher for hospitals that had done so because the cases referred to these physicians had been counted as hospital output, whereas the corresponding resource use (i.e. in terms of physicians) had not been considered on the input side. To control for this, we defined the proportion of all hospital beds that had been leased (LEASED BEDS) as a variable in our regression models.

The set of explanatory variables representing the different environmental characteristics were as follows: The most important regressor was the Hirschman-Herfindahl index (HHI), which measures competitive pressure in a hospital's market, a standard economic measure of market

16

concentration. The market area was defined as the county in which a hospital was located, which is a frequently used definition in hospital studies (Chang *et al.*, 2004; Rosko 1999, 2001, 2004; Rosko and Chilingerian, 1999). Although there has been some controversy about the most appropriate way to define a hospital's market area, Garnick *et al.* (1987) reported that for the purpose of measuring competitive activity it makes little difference whether a hospital's market is defined as a county or a radius. The HHI is obtained by squaring a hospital's regional market share (reflected by the distribution of treated cases) and subsequently summing the market shares of admissions for all of the hospitals in a given county. The higher the HHI, the more concentrated the regional market. We used HHI to measure the effects from the changes over time in a hospital's competitive environment. This specification allowed us to differentiate between the effects of privatization and the effects of changes in market structure resulting from health care reforms.

In recent years, the most significant reform in the German hospital market was the introduction of a new system of reimbursement based on DRGs. The chief motivation behind this fundamental overhaul of the old reimbursement system, which was based on per diem charges, was to create financial incentives that would increase hospital efficiency (Schreyögg *et al.*, 2006). We thus defined a dummy variable (DRG), which was assigned a value of 1 in the DRG era (i.e. 2003 through 2007).

These variables for hospital and environmental characteristics were also used in the propensity score model, as were the case-mix index (CMXI) derived from the Elixhauser Comorbidity Index (van Walraven *et al.*, 2009) and the pre-privatization efficiency (EFFICIENCY) of privatized and non-privatized hospitals. We used this last variable to minimize potential bias because public

17

entities may prefer to sell hospitals characterized by lower levels of efficiency while keeping those that are performing well. Table 4 shows the descriptive statistics for the variables used in the second stage analysis stratified according to the intervention and control groups.

------------------------------
Insert Table 4 about here
------------------------------


## 5. Findings and discussion


Table 5 shows the degree of imbalance before and after propensity score matching for our subset of covariates (interactions are not shown).

------------------------------
Insert Table 5 about here
------------------------------


The differences in covariate means between the unmatched samples indicate that it was especially the size of non-privatized hospitals (in terms of beds) that was likely to be larger than that of privatized hospitals. After propensity score matching, the differences in covariate means between the privatized and non-privatized hospitals were substantially smaller than those seen in the pre-matching distribution. All of the differences between the groups were less than 6% in the post-matching distribution. Table 6 summarizes the results of Hotelling's T-square test. Reassuringly, the balancing conditions were satisfied within each propensity score quartile (i.e. the $P$ values for all quartiles were substantially higher than 0.10).

------------------------------
Insert Table 6 about here
------------------------------

The fixed and random effects regression results for our first model, which used DEA efficiency scores as dependent variable, are summarized in Table 7 and stratified according to whether public hospitals were converted to private for-profit or private non-profit status. Two sets of regression results are shown for each type of conversion: one based on the unmatched samples and the other based on the samples after propensity score matching. The coefficients shown in Table 7 are those for the difference-in-difference interaction between the variables PRIV and POST and can be interpreted as marginal effects. The interaction terms identify the changes in efficiency after a hospital was privatized relative to changes in efficiency in the comparator group.

The regression results for public hospitals that were converted to private for-profit status show that there was a significant increase in efficiency compared to the control group starting the second year after privatization. Throughout all estimations of our efficiency model, the effects of this change in status increased with the number of years after privatization. For instance, four years after their conversion to private for-profit status, the formerly public hospitals experienced an increase in efficiency that was 3.2 to 5.4% greater than that seen among non-privatized hospitals over the same period. These fixed effects regression results are confirmed by similar results obtained through our estimations based on the random effects specification of the model. In the matched samples, the standard errors were larger than in the pre-matched sample. This can be attributed, in part, to the smaller size of the control group; nevertheless, the general finding remained the same. The estimations also suggest that the increase in efficiency seen in public hospitals that were converted to private for-profit status is permanent and not simply a transitional phenomenon after which hospital operations revert to their pre-privatization state.

The regression results for public hospitals that were converted to private non-profit status show that, at least in the first year after privatization, there was a significant increase in efficiency of 3.2 to 4.7% compared to the control group. For years 2 through 4 after privatization, we observed no significant effects apart from those seen in year 2 in the random effects specification with matched samples. In that model, public hospitals converted to private non-profit status showed a significant increase in efficiency of 3.9% in the second year after privatization compared to the non-privatized hospitals. Throughout most estimations, however, the effects of a conversion to private non-profit status decreased as the number of years after privatization increased. This points to a transitory rather than a permanent effect.

------------------------------
Insert Table 7 about here
------------------------------

To gain a better understanding of these findings and the restructuring that occurred after hospitals were converted to private for-profit and non-profit status in our sample, we conducted a series of exploratory regressions. Using the same model specification to identify the effect of privatization on the quantity and type of resource use (i.e. employing input variables from the first-stage analysis as dependent variables of the second-stage regression), we found that hospitals that were converted to private for-profit status substantially reduced all of the analyzed labor inputs during the post-privatization period with the exception of physicians (i.e. nursing staff, other clinical staff, administrative staff, and other nonclinical staff). This finding can potentially be explained by the two lines of internal authority – medical and managerial – that characterize most hospitals: In contrast to nurses and technical staff, physicians are often part of the top management and make decisions on the allocation of resources. Being clinicians or former clinicians themselves,

members of top management may be predisposed to avoiding reductions in the number of physicians. Another explanation may be that avoiding physician lay-offs is a strategy to reduce resistance to change by compensating physicians for coping with the organizational adjustments associated with privatization. For hospitals converted to non-profit status reductions of labor input tend to be smaller compared to conversions to for-profit status.

To explore our results yet further, we examined the interaction effects between a given privatization (difference-in-difference coefficient) and the competitive environment (HHI) in which this privatization took place. In their summary of the theoretical literature, Sheshinski and López-Calva (2003) argue that privatized organizations are likely to have lower efficiency gains in non-competitive markets than they would under the discipline of a competitive market. They assume that organizations in monopolistic or oligopolistic markets restrict output and have higher average costs and lower efficiency than competitive organizations. Rosko (1999, 2001, 2004) and Rosko and Chilingerian (1999), however, have found that efficiency in the US hospital sector is negatively related to market competition. Using HHI as a proxy for competition in our present study, we were unable to observe any effect of this variable on efficiency after privatization.

We also examined the interaction effects between privatization and the introduction of yardstick competition through DRGs in the year 2004 in Germany. There is reason to believe that efficiency gains are larger for privatizations after the introduction of yardstick competition, especially in the case of hospitals converted to private for-profit status (Schreyögg *et al.*, 2006; Biørn *et al.*, 2003; Kjerstad, 2003; Shleifer, 1985). We used a dummy variable to model the pre-DRG and the DRG period. In doing so, we defined each of the years 2001 through 2004 as the cut-off point between pre-DRG and DRG periods because hospitals may have changed their

behavior after the introduction of DRGs or beforehand based on their knowledge of the new system and its upcoming implementation. Table 8 summarizes the corresponding regression results based on a fixed effects model.

-------------------------------
Insert Table 8 about here
-------------------------------

The regression results for hospitals that were converted to private for-profit status reveal a significant negative association between post-privatization performance and the introduction of DRGs. In particular, the efficiency gains seen in hospitals converted to private for-profit status were substantially lower in the DRG era compared to those seen in the control group. The introduction of DRGs induced yardstick competition in the German hospital market, setting strong incentives to increase efficiency and stimulating restructuring efforts across all types of ownership. Our findings thus suggest that it became more challenging for hospitals that were converted to private for-private status in the DRG era to realize further efficiency gains. In the model estimated for hospitals that were converted to private non-profit status, the interaction term between post-privatization performance and the introduction of DRGs was not significant.

We tested the robustness of our findings in several ways. First, we employed the average in-hospital mortality rate as an additional output to adjust for variations in the quality of care between hospitals. The results of our quality-adjusted efficiency model show that employing in-hospital mortality as an additional output was not associated with smaller efficiency gains (see Table 9 for the regression results of the quality-adjusted efficiency model). In fact, the regression results for hospitals that were converted to private for-profit status showed that there was even a small increase in coefficients compared to the estimations of the efficiency model. Our findings

22

therefore do not provide any evidence that increases in technical efficiency come at the expense of the quality of care. This may be due to a decrease over the past decade in the asymmetry of information about the quality of care in the German hospital sector following several health care reforms that have aimed to improve quality assurance, such as the introduction of mandatory quality reports. Furthermore, it is important to consider that privatized hospitals are often located in very competitive regions with substantial overcapacities, which may increase the importance of quality of care as a parameter of competition. Indeed, there is evidence that private for-profit hospitals have improved their quality management and hospital outcomes precisely in order to attract patients in such settings (Busse *et al.*, 2009).

------------------------------
Insert Table 9 about here
------------------------------

Second, we re-estimated all second-stage regressions by incorporating firm fixed effects as an additional dimension. To do so, we estimated time and firm fixed effects as a multi-way clustered regression (Cameron *et al.*, 2006). This resulted in only minor changes in the difference-in-difference coefficients, and our findings remained robust throughout the models. Third, in other economic sectors, Parker and Martin (1995) found that pre-privatization gains in efficiency can be even larger than post-privatization gains. Based on this finding, there is reason to assume that local governments make efforts to increase the efficiency of public hospitals prior to privatization to generate higher sales revenue, reducing potential gains in efficiency after privatization. In order to take account of this possibility, we re-ran our models, allowing an alternative pre-privatization period of two years. The direction of the difference-in-difference coefficients did not change throughout the models, and standard errors increased only slightly due to the reduced sample size. Bias due to pre-privatization efficiency gains was thus unlikely.

23

Our study has a number of strengths compared to previous investigations of hospital ownership conversions. First, to our knowledge, it is the first quantitative study to examine the effects of privatization on technical efficiency using a panel data approach based on bootstrapped DEA efficiency scores. Second, our study employs a difference-in-difference matching approach to address problems arising both from causal inference and time-invariant differences. Third, our sample of privatized hospitals is large ($n = 132$), providing greater statistical power and more robust estimates than the analyses conducted in previous studies. Finally, our sample is rich, consisting of a large set of environmental and organizational characteristics. This is likely to have yielded more consistent results because it allowed us to control appropriately for determinants of efficiency other than the privatization event.

Our study also has several important limitations. First, additional inputs (e.g., capital) and additional outputs (e.g., hospital outpatient cases) would have improved our model of the hospital production process. Considering the number of hospital outpatient cases in addition to inpatient cases is often recommended in order to measure patient care output (Jacobs *et al.*, 2006). Although we had intended to include a proxy for hospital outpatient activities in our analysis (e.g., outpatient surgery), data inconsistencies and measurement errors prevented us from doing so. Second, including explanatory factors in addition to environmental and organizational characteristics might have provided a better explanation of variation in our estimates, thus potentially affecting our interpretation of the relationship between privatization and organizational efficiency. Third, our study relies on in-hospital mortality data and does not take post-hospital mortality into account, which clearly would have been preferable. This being said, Rosenthal *et al.* (2000) found that (a) in-hospital mortality data were not biased by discharge

practices and (b) using in-hospital mortality as a measure of a hospital's quality of care leads to results similar to those obtained with 30 days post-hospital mortality. Fourth, for sensitivity purposes it would have been preferable to use SFA in addition to DEA. When comparing DEA to SFA, however, Linna (1998) and Webster *et al.* (1998) found that both methods yielded comparable results when measuring hospital efficiency. Finally, in DEA model II, we used 1 minus the in-hospital mortality rate per year, which represents an index variable. Syrjänen (2004) found that mixing index and volume measures in DEA may lead to biased results for the most commonly used constant returns to scale variant of the Banker and Moorey (BM) model and Charnes, Cooper, and Rhodes (CCR) model. This problem does not apply in our context, however, because we used a variable returns to scale variant of the BCC model (Hollingsworth and Smith, 2003; Syrjänen, 2004).


## 6. Conclusions


In the present study, we investigated the post-acquisition effects of privatization on hospital efficiency in Germany. Our findings show that hospitals converted to private for-profit status showed an increase in efficiency after privatization that was significantly higher than that realized by their non-privatized counterparts over the same period. We defined four alternative post-privatization periods (i.e. first, second, third, and fourth year) and found that the increase in efficiency after conversion to private for-profit status did not appear to be transitory. Our results show that hospitals that were converted to private for-profit status realized their substantial efficiency gains by markedly reducing all labor inputs (with the exception of physicians) and expenditure on supplies. The results of our study, which remained robust when considering in-hospital mortality as an additional output, do not support frequently voiced concerns that

25

efficiency gains after conversion to private for-profit status are realized at the expense of quality of care. Taking the effect of the introduction of DRG payments into account, it is striking that the efficiency gains of hospitals converted to private for-profit status were significantly lower during the DRG era. We also observed an increase in efficiency one year after hospitals were converted to private non-profit status, but our estimations suggest that this effect is transitory and that hospitals converted to private for-profit status follow a different restructuring strategy than that pursued by their private non-profit counterparts.

Our results indicate that converting hospitals to private for-profit status may be an effective way to ensure better allocation of resources in the hospital sector. Before drawing policy implications, however, a number of issues must be considered. In some cases, public hospitals converted to private non-profit status may not be restructured with the intention of increasing efficiency, but rather with the aim of improving the patient experience, including the quality of care. Although our results remained robust when considering in-hospital mortality for hospitals converted to private non-profit status, other measures not considered in our analysis, such as patient satisfaction, may have led to different results after the privatization event. Moreover, it should also be taken into consideration that the time needed to develop new quality assurance systems in privatized hospitals may be longer than the period we considered in our study. Additional research is needed to investigate the long-term effects of privatization and to examine the decisions behind the approaches taken by private for-profit and private non-profit organizations in their restructuring of public hospitals.

Given the increasing importance of privatization in health systems in Germany and beyond, further studies are needed to investigate the effects of privatization on efficiency and different

dimensions of care quality. Outside the hospital sector, privatization activity is also increasing in laboratory diagnostics, nursing care and rehabilitative services. The approach used in our study may be useful in investigating privatization in these other areas of care.

## 7. References

Austin PC. 2008. A critical appraisal of propensity-score matching in the medical literature between 1996 and 2003. *Statistics in Medicine* 27: 2037–2049.

Austin PC. 2009. Some methods of propensity-score matching had superior performance to others: results of an empirical investigation and Monte Carlo simulations. *Biometrical Journal* **51**: 171–184.

Banker R, Charnes A, Cooper W. 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science* **30**: 1078–1092.

Biørn E, Hagen TP, Iversen T *et al.* 2003. The effect of activity-based financing on hospital efficiency: A panel data analysis of DEA efficiency scores 1992-2000. *Health Care Management Science* **6**: 271–283.

Blundell R, Dias MC. 2000. Evaluation methods for non-experimental data. *Fiscal Studies* **21**: 427–468.

Bös D. 1991. *Privatization: a theoretical treatment*. Oxford University Press: Oxford.

Boycko M, Shleifer A, Vishny R. 1996. A theory of privatisation. *The Economic Journal* **106**: 309–319.

Burgess J, Wilson P. 1998. Variation in inefficiency among US hospitals. *Information Systems and Operational Research* **36**: 84–102.

Busse R, Nimptsch U, Mansky T. 2009. Measuring, Monitoring, and Managing Quality in Germany's Hospitals. *Health affairs* **28**: 294–304.

Cameron AC, Gelbach JB, Miller DL. 2006. Robust Inference with Multi-Way Clustering. *NBER Technical Working Paper No. 327*, University of California, Berkely.

Carey K, James F, Burgess JF Jr. 1999. On measuring the hospital cost/quality trade-off. *Health Economics* **8**: 509–520.

Carey K. 2000. A multilevel modelling approach to analysis of patient costs under managed care. *Health Economics* **9**(5): 435–446.

Carey K. 2002. Hospital Length of Stay and Cost: A Multilevel Modeling Analysis. *Health Services and Outcomes Research Methodology* **3**: 41–56.

Chang H, Chang WJ, Das S, Li SS. 2004. Health care regulation and the operating efficiency of hospitals: Evidence from Taiwan. *Journal of Accounting and Public Policy* **23**: 483–510.

Coelli T, Rao D, Batteese G. 1999. *An Introduction to Efficiency and Productivity Analysis*. Kluwer Academic Publishers: Boston.

Dudley, R., Johansen, K., Brand, R., Rennie, D., Milstein, A., 2000. Selective referral to high-volume hospitals: estimating potentially avoidable deaths. *Journal of the American Medical Association* **283**: 1159–1166.

Dyson R, Allen R, Camanho A *et al*. 2001. Pitfalls and protocols in DEA. *European Journal of Operational Research* **132**: 245–259.

Farsi M. 2004. Changes in hospital quality after conversion in ownership status. *International Journal of Health Care Finance and Economics* **4**: 211–230.

Federal Statistical Office of Germany. 2009. Fachserie 12 Reihe 6.1.1 - Grunddaten der Krankenhäuser und Vorsorge- oder Rehabilitationseinrichtungen. http://www.destatis.de/jetspeed/portal/cms/Sites/destatis/Internet/DE/Content/Publikationen /Fachveroeffentlichungen/Gesundheit/Krankenhaeuser/GrunddatenKrankenhaeuser,templat eId=renderPrint.psml [24 February 2011]

Garnick D, Luft H, Robinson J *et al*. 1987. Appropriate measures of hospital market areas. *Health Services Research* **22**: 69–89.

Girma S, Görg H. 2007. Evaluating the foreign ownership wage premium using a difference-in-differences matching approach. *Journal of International Economics* **72**: 97–112.

Harrison JP, Coppola MN, Wakefield M. 2004. Efficiency of federal hospitals in the United States. *Journal of Medical Systems* **28**: 411–422.

Haskel J, Szymanski S. 1993. Privatization, Liberalization, Wages and Employment: Theory and Evidence for the UK. *Economica* **60**: 161–182.

Heckman JJ, Ichimura H, Todd PE. 1997. Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *Review of Economic Studies* **64**: 605–654.

Heckman JJ, Hotz VJ. 1989. Choosing among Alternative Nonexperimental Methods for Estimating the Impact of Social Programs: The Case of Manpower Training. *Journal of American Statistical Association* **84**: 862–880.

Herr A. 2008. Cost and technical efficiency of German hospitals: does ownership matter?. *Health Economics* **17**:1057-1071.

Hollingsworth B. 2008. The measurement of efficiency and productivity of health care delivery. *Health Economics* **17**: 1107–1128.

Hollingsworth B, Smith P. 2003. Use of ratios in data envelopment analysis. *Applied Economics Letters* **10**: 733-735.

Imai K, King G, Stuart E. 2008. Misunderstandings among experimentalists and observationalists about causal inference. *Journal of the Royal Statistical Society* **171**: 481–502.

Jacobs R, Smith PC, Street A. 2006. *Measuring Efficiency in Health Care: Analytic Techniques and Health Policy*. Cambridge University Press: Cambridge.

Kjerstad EM. 2003. Prospective funding of general hospitals in Norway – incentives for higher production?. International Journal of Health Care Finance and Economics **3**: 231-251.

Laffont JJ, Tirole J. 1993. Privatization and incentives. In *A theory of incentives in procurement and regulation*, Laffont JJ, Tirole J (eds.). MIT Press: Cambridge.

Linna M. 1998. Measuring hospital cost efficiency with panel data models. *Health Economics* **7**: 415–427.

Megginson WL, Nash RC, van Randenborgh M. 1994. The Financial and Operating Performance of Newly Privatized Firms: An International Empirical Analysis. *Journal of Finance* **49**: 403–452.

Parker D, Martin S. 1995. The Impact of UK Privatization on labor and total factor productivity. *Scottish Journal of Political Economy* **42**: 201–220.

Pestieau, P. (2009), Assessing the performance of the public sector. *Annals of Public and Cooperative Economics* **80**: 133–161.

Picone G, Chou S, Sloan F. 2002. Are for-profit hospital conversions harmful to patients and to Medicare? *RAND Journal of Economics* **33**: 507–523.

Pilyavsky AI, Aaronson WE, Bernet PM *et al*. 2006. East-west: does it make a difference to hospital efficiencies in Ukraine? *Health Economics* **15**: 1173–1186.

Research Data Centre of the Statistical Offices of the Länder. 2009. Krankenhausstatistik (Teil I: Grunddaten, Teil II: Diagnosen und Teil III: Kostennachweis) der Jahre 1996–2008, Antrag 1133-2009.

Rosenbaum P. 1989. Optimal matching for observational studies. *Journal of the American Statistical Association* **84**: 1024–1032.

Rosenbaum P. 2002. *Observational studies*. Springer: New York.

Rosenthal GE, Baker DW, Norris DG *et al*. 2000. Relationships between in-hospital and 30-day standardized hospital mortality: implications for profiling hospitals. *Health Services Research* **34**: 1449–1468.

Rosko MD. 1999. Impact of internal and external environmental pressures on hospital inefficiency. *Health Care Management Science* **2**: 63–74.

Rosko MD. 2001. Cost efficiency of US hospitals: a stochastic frontier approach. *Health Economics* **10**: 539–551.

Rosko MD. 2004. Performance of US teaching hospitals: a panel analysis of cost inefficiency. *Health Care Management Science* **7**: 7–16.

Rosko MD, Chilingerian JA. 1999. Estimating hospital inefficiency: does case mix matter? *Journal of Medical Systems* **23**: 57–71.

Rubin DB. 1973. The use of matched sampling and regression adjustment to remove bias in observational studies. *Biometrics* **29**: 185–203.

Rubin DB. 2006. *Matched Sampling for Causal Effects*. Cambridge University Press: New York.

Sappington D, Stiglitz J. 1987. Privatization, information and incentives. *Journal of Policy Analysis and Management* **6**: 567–582.

Schmidt K. 1996. The costs and benefits of privatization: an incomplete contracts approach. *Journal of Law, Economics, and Organization* **12**: 1–24.

Schreyögg J, Tiemann O, Busse R. 2006. Cost accounting to determine prices: how well do prices reflect costs in the German DRG-system? *Health Care Management Science* **9**: 269–279.

Schreyögg J, Stargardt T, Tiemann O. 2010. Costs and Quality of Hospitals in Different Health Care Systems: a Multilevel Approach with Propensity Score Matching. *Health Economics* **20**(1): 85–100.

Shen YC. 2002. The effect of hospital ownership choice on patient outcomes after treatment for acute myocardial infarction. *Journal of Health Economics* **21**: 901–922.

Shen YC. 2003. Changes in hospital performance after ownership conversions. *Inquiry* **40**: 217–34.

Shen YC, Eggleston K, Lau J *et al*. 2007. Hospital ownership and financial performance: what explains the different findings in the empirical literature? *Inquiry* **44**: 41–68.

Sheshinski E, López-Calva L. 2003. Privatization and its benefits: theory and evidence. *CESifo Economic Studies* **49**: 429–459.

Shleifer A. 1985. A theory of yardstick competition. *RAND Journal of Economics* **16**: 319–327.

Shleifer A, Vishny RW. 1994. Politicians and Firms. *Quarterly Journal of Economics* **109**: 995–1025.

Simar L, Wilson PW. 1998. Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science* **44**: 49–61.

Simar L, Wilson PW. 2000. A general methodology for bootstrapping in non-parametric frontier models. *Journal of Applied Statistics* **27**: 779–802.

Simar L, Wilson PW. 2007. Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics* **136**: 31–64.

Smith JE, Todd P. 2005. Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics* **125**: 305–353.

Syrjänen MJ. 2004. Non-discretionary and discretionary factors and scale in data envelopment analysis. *European Journal of Operational Research* **158**: 20–33.

Tiemann O, Schreyögg J. 2009. Effects of ownership on hospital efficiency in Germany. *Business Research* **2**: 115–145.

van Walraven C, Austin P, Jennings A *et al*. 2009. A Modification of the Elixhauser Comorbidity Measures into a Point System for Hospital Death Using Administrative Data. *Medical Care* **47**: 626–633.

Vickers J, Yarrow G. 1991. Economic perspectives on privatization. *The Journal of Economic Perspectives* **5**: 111–132.

Villalonga B. 2000. Privatization and efficiency: differentiating ownership effects from political, organizational, and dynamic effects. *Journal of Economic Behavior and Organization* **42**: 43–74.

Webster R, Kennedy S, Johnson L. 1998. Comparing techniques for measuring efficiency and productivity of Australian private hospitals. *Working Paper 1351.0*, Australian Bureau of Statistics Catalogue.

**TABLE 1**

**Outline of the statistical analysis**

| Steps | Implementation | Sample Size |
|---|---|---|
| 1. Increasing homogeinity of the | To ensure the comparability of the hospitals in the sample we | Randomly selected data from 1,878 German acute care hospitals were obtained between 1996 and 2008 |
| | (1) Excluded hospitals providing only psychiatric care, university hospitals, day clinics, hospitals with fewer than 50 beds and more than 2,000 beds | A total of 1,187 hospitals remained in the sample |
| | (2) Excluded non-privatized non-profit and private for-profit hospitals during our study period | A total of 548 hospitals remained in the sample |
| | (3) Eliminated hospitals with measurement errors and hospitals that had observations in less than 7 years between 1996-2008 | A total of 493 hospitals remained in the sample |
| 2. Identification of interventrion and control groups | Seperation of intervention and control groups | Intervention group: 132 privatized hospitals were found, i.e. 99 public hospitals were acquired by a private for-profit hospitals and 33 public hospitals were acquired by private non-profit Control group: 361 public hospitals |
| 3. Data Envelopment Analysis (DEA) | Application of an input-oriented variable returns to scale model by Banker, Charnes, and Cooper (BCC) for all privatized and non-privatized hospitals. DEA was performed per year. | |
| 4. Bootstrapping | Derive bias-corrected DEA efficiency scores from 500 bootstrap iterations | |
| 5. Proponsity Score Matching (PSM) | (1) Estimate probability for being privatized based on our defined covariates by means of logistic regression | |
| | (2) Match privatized hospitals to non-privatized public hospitals based on predicted means by using a one-to-one matching with replacement; we used an optimal matching algorithm i.e. we minimized the total distance of matched pairs | Number of hospitals in control group after matching: 128 in first year after matching, 113 in second year after matching, 99 in third year after matching, 86 in fourth year after matching |
| 6. PSM Diagnostics | Assessing appropriateness and reliability of the PSM results by using (1) standardized differences and (2) Hotelling's T-square statistic based on quartiles | |
| 7. Regression Analysis | Use of fixed and random effects linear regression model for truncated longitudinal data with DEA efficiency scores as dependent variable. Difference-in-difference interaction was used to examine effects of privatization on efficiency compared to control group of non-privatized hospitals controlling for patient heterogeneity and the impact of hospital organizational and environmental characteristics | |
| 8. Sensitivity analysis | (1) Re-estimation of the DEA model by employing 1-MORTALITY as a second output (2) Estimated multiway clustered regression including time and firm fixed effects (3) Allowed pre-privatization period of two years instead of one year | |

**TABLE 2**

**Number of hospital privatizations per year**

| Period | Number of privatizations | | |
|---|---|---|---|
| | **Total** | **Non-profit** | **For-profit** |
| 1997 | 15 | 5 | 10 |
| 1998 | 13 | 8 | 5 |
| 1999 | 7 | 0 | 7 |
| 2000 | 4 | 2 | 2 |
| 2001 | 15 | 0 | 15 |
| 2002 | 13 | 2 | 11 |
| 2003 | 14 | 3 | 11 |
| 2004 | 11 | 2 | 9 |
| 2005 | 13 | 1 | 12 |
| 2006 | 16 | 2 | 14 |
| 2007 | 11 | 8 | 3 |
| **Total** | **132** | **33** | **99** |

**TABLE 3**

**Descriptive statistics of in- and outputs for the matched sample**

| Period | T-1 | | T+1 | | T+2 | | T+3 | | T+4 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| *For-profit* | | | | | | | | | | |
| Number of hospitals | n=99 | | n=99 | | n=90 | | n=77 | | n=66 | |
| PHYS | 71.46 | (73.12) | 73.32 | (74.91) | 71.74 | (72.76) | 70.47 | (75.18) | 74.97 | (79.41) |
| NURSE | 199.7 | (168.4) | 188.9 | (165.2) | 179.3 | (153.9) | 173.2 | (153.8) | 177.3 | (154.7) |
| CLIN | 127.1 | (125.8) | 126.7 | (126.2) | 118.5 | (118.9) | 114.5 | (117.8) | 120.5 | (121.8) |
| ADMIN | 33.55 | (29.81) | 33.48 | (28.27) | 31.85 | (26.78) | 30.98 | (26.50) | 30.94 | (26.17) |
| NONCLIN | 66.07 | (57.01) | 56.84 | (54.95) | 48.97 | (47.75) | 45.20 | (47.25) | 43.07 | (45.14) |
| SUPPLIES | 14.5 | (15.7) | 15.1 | (15.7) | 15.3 | (15.3) | 14.7 | (14.5) | 16.1 | (15.9) |
| INPATIENT | 13147 | (10860) | 13386 | (11286) | 13002 | (10649) | 12822 | (11142) | 13537 | (11780) |
| 1-MORTALITY | 0.974 | (0.011) | 0.975 | (0.010) | 0.975 | (0.010) | 0.976 | (0.010) | 0.976 | (0.009) |
| *Non-profit* | | | | | | | | | | |
| Number of hospitals | n=33 | | n=33 | | n=24 | | n=23 | | n=22 | |
| PHYS | 40.64 | (41.08) | 42.82 | (44.35) | 49.04 | (50.40) | 52.54 | (53.04) | 55.56 | (54.46) |
| NURSE | 132.1 | (119.5) | 128.6 | (122.4) | 14.4 | (137.62) | 151.7 | (134.9) | 156.4 | (133.7) |
| CLIN | 78.3 | (84.92) | 78.8 | (84.97) | 91.4 | (97.96) | 96.3 | (99.66) | 100.7 | (100.8) |
| ADMIN | 22.98 | (21.42) | 22.57 | (23.74) | 27.01 | (29.52) | 27.37 | (29.45) | 28.67 | (29.85) |
| NONCLIN | 60.05 | (62.30) | 56.37 | (62.85) | 64.05 | (77.76) | 59.64 | (75.01) | 59.73 | (77.96) |
| SUPPLIES | 7.8 | (6.7) | 8.3 | (7.3) | 9.0 | (8.6) | 10.1 | (9.2) | 10.6 | (10.1) |
| INPATIENT | 8232 | (6668) | 8631 | (7358) | 9773 | (8526) | 12093 | (8612) | 10316 | (8607) |
| 1-MORTALITY | 0.978 | (0.009) | 0.978 | (0.011) | 0.977 | (0.009) | 0.976 | (0.010) | 0.977 | (0.009) |
| *Control* | | | | | | | | | | |
| Number of hospitals | n=128 | | n=128 | | n=113 | | n=99 | | n=87 | |
| PHYS | 65.50 | (72.50) | 69.62 | (76.55) | 72.73 | (79.68) | 71.65 | (84.07) | 69.66 | (80.05) |
| NURSE | 189.0 | (172.8) | 187.2 | (168.4) | 191.1 | (169.9) | 183.8 | (165.5) | 181.3 | (166.8) |
| CLIN | 119.4 | (141.5) | 120.5 | (140.7) | 124.2 | (143.5) | 119.7 | (139.4) | 121.6 | (146.9) |
| ADMIN | 32.70 | (33.05) | 33.08 | (33.47) | 33.49 | (34.57) | 31.57 | (32.83) | 32.11 | (34.43) |
| NONCLIN | 73.81 | (77.88) | 68.42 | (71.34) | 68.27 | (71.91) | 66.26 | (71.47) | 65.35 | (71.25) |
| SUPPLIES | 12.0 | (13.4) | 13.6 | (15.5) | 14.5 | (16.8) | 14.3 | (17.6) | 14.6 | (19.6) |
| INPATIENT | 12435 | (10516) | 12606 | (10587) | 13049 | (10984) | 12630 | (10736) | 12594 | (11278) |
| 1-MORTALITY | 0.973 | (0.013) | 0.973 | (0.013) | 0.974 | (0.011) | 0.973 | (0.013) | 0.973 | (0.012) |

**TABLE 4**

**Descriptive statistics of variables used for the second stage analysis for the matched sample**

| Period | T-1 | | T+1 | | T+2 | | T+3 | | T+4 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| *For-profit* | | | | | | | | | | |
| Number of hospitals | n=99 | | n=99 | | n=90 | | n=77 | | n=66 | |
| BEDS | 344 | (268) | 344 | (273) | 332 | (261) | 327 | (262) | 342 | (272) |
| LEASED BEDS | 0.037 | (0.074) | 0.032 | (0.073) | 0.028 | (0.050) | 0.026 | (0.047) | 0.024 | (0.047) |
| TEACHING | 0.146 | (0.154) | 0.171 | (0.177) | 0.162 | (0.191) | 0.177 | (0.202) | 0.129 | (0.147) |
| CMXI | 0.161 | (0.063) | 0.155 | (0.061) | 0.160 | (0.056) | 0.154 | (0.052) | 0.147 | (0.048) |
| EFFICIENCY | 0.761 | (0.122) | 0.757 | (0.121) | 0.772 | (0.123) | 0.774 | (0.114) | 0.772 | (0.117) |
| HHI | 0.399 | (0.294) | 0.393 | (0.284) | 0.413 | (0.291) | 0.450 | (0.288) | 0.443 | (0.267) |
| *Non-profit* | | | | | | | | | | |
| Number of hospitals | n=33 | | n=33 | | n=24 | | n=23 | | n=22 | |
| BEDS | 237 | (179) | 232 | (189) | 264 | (220) | 267 | (214) | 274 | (216) |
| LEASED BEDS | 0.060 | (0.067) | 0.055 | (0.064) | 0.037 | (0.047) | 0.039 | (0.047) | 0.055 | (0.097) |
| TEACHING | 0.151 | (0.156) | 0.165 | (0.159) | 0.141 | (0.151) | 0.182 | (0.125) | 0.099 | (0.138) |
| CMXI | 0.141 | (0.042) | 0.146 | (0.044) | 0.142 | (0.043) | 0.128 | (0.034) | 0.132 | (0.037) |
| EFFICIENCY | 0.730 | (0.144) | 0.757 | (0.131) | 0.743 | (0.129) | 0.738 | (0.140) | 0.716 | (0.157) |
| HHI | 0.404 | (0.210) | 0.439 | (0.253) | 0.463 | (0.274) | 0.469 | (0.278) | 0.475 | (0.285) |
| *Control* | | | | | | | | | | |
| Number of hospitals | n=128 | | n=128 | | n=113 | | n=99 | | n=87 | |
| BEDS | 332 | (257) | 329 | (256) | 336 | (257) | 321 | (248) | 319 | (250) |
| LEASED BEDS | 0.048 | (0.078) | 0.045 | (0.078) | 0.047 | (0.083) | 0.043 | (0.078) | 0.051 | (0.094) |
| TEACHING | 0.148 | (0.153) | 0.146 | (0.158) | 0.148 | (0.158) | 0.142 | (0.154) | 0.146 | (0.160) |
| CMXI | 0.162 | (0.072) | 0.162 | (0.070) | 0.160 | (0.067) | 0.154 | (0.050) | 0.157 | (0.061) |
| EFFICIENCY | 0.765 | (0.127) | 0.746 | (0.121) | 0.750 | (0.129) | 0.747 | (0.133) | 0.747 | (0.119) |
| HHI | 0.390 | (0.231) | 0.394 | (0.241) | 0.395 | (0.242) | 0.390 | (0.249) | 0.398 | (0.247) |

**TABLE 5**

**Balance in measured covariates before and after matching**

| Group | Unmatched sample | | | | | Matched sample | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Control (n=361) | | Intervention (n=132) | | | Control (n=128) | | Intervention (n=132) | | |
| | Mean | SD | Mean | SD | $d_i$ | Mean | SD | Mean | SD | $d_i$ |
| **Variable name** | | | | | | | | | | |
| BEDS | 351 | (259) | 317 | (252) | 12.89% | 332 | (257) | 317 | (252) | 5.68% |
| LEASED BEDS | 0.069 | (0.091) | 0.043 | (0.073) | 2.60% | 0.048 | (0.078) | 0.043 | (0.073) | 0.50% |
| TEACHING | 0.169 | (0.172) | 0.147 | (0.154) | 2.20% | 0.148 | (0.153) | 0.147 | (0.154) | 0.10% |
| CMXI | 0.157 | (0.058) | 0.156 | (0.059) | 0.10% | 0.162 | (0.072) | 0.156 | (0.059) | 0.60% |
| EFFICIENCY | 0.772 | (0.111) | 0.753 | (0.128) | 1.90% | 0.765 | (0.127) | 0.753 | (0.128) | 1.20% |
| HHI | 0.401 | (0.242) | 0.400 | (0.275) | 0.10% | 0.390 | (0.231) | 0.400 | (0.275) | 1.00% |

**TABLE 6**

**Results from Hotelling's T square test by propensity score quartile**

| Quartile | T squared statistics | *F* test statistics | *P* values |
|---|---|---|---|
| FIRST | 3.593 | 0.551 | 0.768 |
| SECOND | 4.647 | 0.712 | 0.641 |
| THIRD | 4.066 | 0.615 | 0.717 |
| FOURTH | 4.933 | 0.746 | 0.615 |

**TABLE 7**

**Regression results for the efficiency model**

| | Public->For-profit | | | | Public->Non-profit | | | |
|---|---|---|---|---|---|---|---|---|
| | *Coefficients* | | | | | | | |
| *Fixed effects* | *Unmatched* | | *Matched* | | *Unmatched* | | *Matched* | |
| 1st year after privatization | 0.003 | (0.008) | 0.016 | (0.012) | 0.033** | (0.014) | 0.041* | (0.023) |
| 2nd year after privatization | 0.019** | (0.009) | 0.034** | (0.013) | 0.015 | (0.016) | 0.035 | (0.025) |
| 3rd year after privatization | 0.025*** | (0.009) | 0.043*** | (0.016) | 0.019 | (0.017) | 0.022 | (0.026) |
| 4th year after privatization | 0.032*** | (0.010) | 0.054*** | (0.016) | 0.002 | (0.017) | 0.012 | (0.027) |
| *Random effects* | | | | | | | | |
| 1st year after privatization | 0.004 | (0.008) | 0.019** | (0.012) | 0.032** | (0.014) | 0.047** | (0.022) |
| 2nd year after privatization | 0.020** | (0.009) | 0.033** | (0.013) | 0.014 | (0.016) | 0.039* | (0.024) |
| 3rd year after privatization | 0.025*** | (0.009) | 0.041*** | (0.016) | 0.018 | (0.017) | 0.038 | (0.025) |
| 4th year after privatization | 0.032*** | (0.010) | 0.051*** | (0.016) | 0.000 | (0.017) | 0.022 | (0.027) |

* $P \leq 0.10$; ** $P \leq 0.05$; *** $P \leq 0.01$; SE in parentheses

**TABLE 8**

**Changes in efficiency after privatization in the DRG era compared to the pre-DRG era**

| Post-privatization period | Matched sample | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | T+1 | | T+2 | | T+3 | | T+4 | |
| *Public->For-profit* | *Coefficients* | | | | | | | |
| 2001 cut-off point | -0.023 | (0.019) | -0.026 | (0.022) | -0.021 | (0.029) | 0.011 | (0.033) |
| 2002 cut-off point | -0.023 | (0.017) | -0.018 | (0.022) | -0.039* | (0.025) | -0.005 | (0.029) |
| 2003 cut-off point | -0.023 | (0.016) | -0.036* | (0.019) | -0.039* | (0.024) | -0.041* | (0.024) |
| 2004 cut-off point | -0.030* | (0.017) | -0.037** | (0.019) | -0.047** | (0.022) | -0.043* | (0.024) |
| *Public->Non-profit* | | | | | | | | |
| 2001 cut-off point | 0.001 | (0.034) | -0.009 | (0.036) | 0.004 | (0.038) | 0.042 | (0.051) |
| 2002 cut-off point | 0.001 | (0.034) | -0.006 | (0.037) | 0.004 | (0.038) | -0.050 | (0.038) |
| 2003 cut-off point | 0.000 | (0.032) | -0.006 | (0.037) | 0.009 | (0.039) | -0.051 | (0.038) |
| 2004 cut-off point | -0.005 | (0.033) | -0.035 | (0.038) | 0.009 | (0.039) | -0.036 | (0.041) |

* $P \leq 0.10$; ** $P \leq 0.05$; *** $P \leq 0.01$; SE in parentheses

**TABLE 9**

**Regression results for the quality-adjusted efficiency model**

| | Public->For-profit | | | | Public->Non-profit | | | |
|---|---|---|---|---|---|---|---|---|
| | | | *Coefficients* | | | | | |
| *Fixed effects* | *Unmatched* | | *Matched* | | *Unmatched* | | *Matched* | |
| $1^{st}$ year after privatization | 0.003 | (0.008) | 0.020* | (0.012) | 0.033** | (0.014) | 0.037 | (0.023) |
| $2^{nd}$ year after privatization | 0.023*** | (0.009) | 0.036*** | (0.013) | 0.014 | (0.016) | 0.033 | (0.024) |
| $3^{rd}$ year after privatization | 0.027*** | (0.009) | 0.044*** | (0.015) | 0.017 | (0.017) | 0.019 | (0.025) |
| $4^{th}$ year after privatization | 0.035*** | (0.010) | 0.058*** | (0.016) | -0.001 | (0.017) | -0.002 | (0.028) |
| *Random effects* | | | | | | | | |
| $1^{st}$ year after privatization | 0.004 | (0.008) | 0.022* | (0.012) | 0.033** | (0.014) | 0.047** | (0.022) |
| $2^{nd}$ year after privatization | 0.024*** | (0.009) | 0.036*** | (0.013) | 0.013 | (0.016) | 0.039* | (0.023) |
| $3^{rd}$ year after privatization | 0.027*** | (0.009) | 0.043*** | (0.015) | 0.017 | (0.017) | 0.037 | (0.024) |
| $4^{th}$ year after privatization | 0.035*** | (0.010) | 0.057*** | (0.016) | -0.010 | (0.017) | 0.011 | (0.027) |

\* $P \leq 0.10$; ** $P \leq 0.05$; *** $P \leq 0.01$; SE in parentheses

# hche

Hamburg Center
for Health Economics

The Hamburg Center for Health Economics is a joint center of the School of Business, Economics and Social Sciences and the Medical School at the University of Hamburg.

Contact:   Hamburg Center for Health Economics
              Von-Melle-Park 5, 20146 Hamburg, Germany
              Tel. +49 (0) 42838-8041, Fax: +49 (0) 42838-8043
              Email: office@hche.eu, http://www.hche.eu

## hche Research Paper Series, ISSN 2191-6233 (Print), ISSN 2192-2519 (Internet)

2011/1   Mathias Kifmann and Kerstin Roeder, Premium Subsidies and Social Insurance: Substitutes or Complements? March 2011

2011/2   Oliver Tiemann and Jonas Schreyögg, Changes in Hospital Efficiency after Privatization. June 2011