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Health systems: changes in hospital efficiency and profitability

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Abstract This study investigates potential changes in hospital performance after health system entry, while differentiating between hospital technical and cost efficiency and hospital profitability. In the first stage we obtained (bootstrapped) data envelopment analysis (DEA) efficiency scores. Then, genetic matching is used as a novel matching procedure in this context along with a difference-in-difference approach within a panel regression framework. With the genetic matching procedure, independent and health system hospitals are matched along a number of environmental and organizational characteristics. The results show that health system entry increases hospital technical and cost efficiency by between 0.6 and 3.4 % in four alternative post-entry periods, indicating that health system entry has not a transitory but rather a permanent effect on hospital efficiency. Regarding hospital profitability, the results reveal an increase in hospital profitability only 1 year after health system entry, and the estimations suggest that this effect is a transitional phenomenon. Overall, health system entry may serve as an appropriate management instrument for decision makers to increase hospital performance.

Keywords Hospital systems · Performance measurement · Profitability · Data envelopment analysis · Genetic matching · Difference-in-difference

1 Introduction

Over the past few decades, the hospital industry has been substantially restructured and consolidated (e.g., by the introduction of DRG or lasting hospital privatization) [1]. Therefore, it is increasingly difficult for independent hospitals to remain in the market. Hospitals have responded to these changes by forming or joining multi-institutional arrangements and by cooperating with other health organizations [2]. It is assumed that hospitals that enter into multi-institutional arrangements can achieve cost savings and efficiency gains through potential economies of scale and scope and synergy effects. Cost savings can be achieved by reducing or consolidating duplicate activities, such as administrative (e.g., accounting) or support (e.g., pharmacy) hospital functions. Hospitals can gain improved access to information in the form of management skills. Moreover, hospitals in multi-institutional arrangements can also achieve efficiency gains. Thus, hospitals may provide a greater range of health services. The access to information in the form of clinical expertise can be enhanced. Moreover, hospitals can gain market power by achieving a competitive advantage over single hospitals. Hospitals that enter into multi-institutional arrangements are assumed to be provided with benefits such as an improved ability to recruit staff, easier access to capital and services, improved skills through information exchanges, and bargaining power [3].

Among multi-institutional arrangements, health systems and health networks are two particularly popular forms of arrangements; both arrangements reflect the complex relationships among hospitals [4]. Health systems involve multiple health organizations that operate under the centralized ownership of key health organizations (i.e., hospitals), whereas health networks are strategic alliances or contractual affiliations between hospitals and other health organizations that provide a diverse range of health services. The primary difference between the two arrangements is that a health system has a single owner, whereas a health network features diversified ownership by affiliated hospitals and other organizations [5, 6]. This study investigates changes in hospital technical and cost efficiency and hospital profitability following a

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hospital's entry into a health system. To investigate these changes, we compare the efficiency and profitability changes of hospitals that enter a health system to those of hospitals that remain independent. In doing so, the analysis proceeds in the following steps:

1) We conduct a Data Envelopment Analysis (DEA) by estimating the technical and cost efficiency of hospitals. Efficiency scores are derived for each hospital within the sample by using (bootstrapped) DEA [7].
2) We employ genetic matching to ensure the comparability of independent and health system hospitals with regard to, e.g., hospital or patient characteristics [8, 9].
3) Using the information derived in steps 1 and 2, we estimate difference-in-difference regression models to investigate whether health system membership improves hospital efficiency and profitability over non-health system membership [10].

This study contributes to the research on health systems in several ways. This is the first study to examine the potential effect of a hospital's entry into a multi-institutional arrangement on hospital performance. From a methodological perspective, we are the first to employ a two-stage approach combining data envelopment analysis (DEA) with a novel matching method – genetic matching – and a difference-in-difference approach in this context. Until now, previous studies on health systems have focused on the US hospital context and have used data from US hospitals, whereas this study is based on German health systems. Comparable to US health systems, German health systems also range from local to regional and national in their geographic scope and vary in size. Moreover, the German hospital sector has a prospective payment system and strong competition that is similar to that in many other countries [e.g., 11]. We exclusively focus on hospital membership in health systems, while membership in hospital networks is not observable.

This paper is organized as follows: The second section summarizes the theoretical rationale and previous empirical literature on the impact of health systems on hospital performance. The third section presents the estimation strategy, including the data and methodology that we use to analyze these relationships. The fourth section describes the results of the data analysis and is followed by the fifth section, which discusses these results. The sixth section draws different conclusions and suggests possibilities for further research.

2 Prior research

Two theoretical perspectives – transaction cost theory and resource dependence theory – guide the research on multi-institutional arrangements, such as health systems and health networks. The motivation to join one of these arrangements is either to gain efficiency by reducing transaction costs [12] or to gain resources and power [13]. Transaction cost theory suggests that cooperation among hospitals can reduce the costs of monitoring and coordination [14, 4], whereas resource dependence theory indicates that hospitals attempt to reduce their dependence on others that control critical resources in their environment by joining multi-institutional arrangements [13].

Bazzoli's taxonomy of health systems and health networks, which was published in 1999 [5] and updated in 2004 by Dubbs [15], has motivated research activities on health systems. In particular, most of the existing literature focuses on the potential effects of hospital membership in health systems on various outcomes, such as hospital efficiency and profitability [e.g., 5, 15, 16].

Existing empirical studies on health systems can be divided into two categories. The first category of empirical studies examines hospitals in health systems and their association with hospital efficiency. Two studies focus on the effect of hospital membership in health systems. Carey [17] finds weak evidence for a positive association between health system membership and hospital cost efficiency. Rosko et al. [1] investigate different types of health systems, particularly centralized and decentralized health systems. They conclude that membership in these different types of health systems can be positively or negatively related to cost inefficiency. Two other studies focus on the impact of hospital services provided at the health system level on hospital efficiency. Proenca and Rosko [4] find that hospitals that provide a moderate to high proportion of their services at the system level are more efficient than hospitals that do not use health systems for service provision. Proenca et al. [18] analyze this effect on cost performance and reveal that the proportion of hospital services provided at the system level is negatively related to hospital costs. Thus, based on the results of these four previous studies on the link between system membership and hospital efficiency, the evidence on this relation is not clear.

The second category of empirical studies focuses on the impact of health system membership on hospital profitability. Bazzoli et al. [19] find that hospitals in moderately centralized health systems have better financial performance than those operating within other types of systems. Using data on US hospitals from 1986 to 1992, Tennyson and Fottler [20] analyze the impact of health system membership on financial performance in two different years. They reveal that financial performance decreases with health system membership in 1986 but that there is no significant impact in 1992. In sum, evidence on the relationship between health system membership and hospital profitability is ambiguous.

Although all the aforementioned empirical studies reveal interesting effects of health system membership, they suffer from several important weaknesses. First, all studies analyzing the effects of health systems are cross-sectional. Only Tennyson and Fottler [20] use data from two different years to investigate the impact of health systems on hospital profitability, but time sequences remain unassessed in the study. To draw any causal implications, a longitudinal data analysis is necessary. Second, the majority of existing studies analyzing the impact of health systems on hospital efficiency have used a similar methodological approach: efficiency studies in this research field analyze cost efficiency solely by using cost function and stochastic frontier analysis (SFA) [e.g., 17, 1]. To the best of our knowledge, no previous study has measured technical efficiency and/or used DEA. Because both DEA and SFA have advantages and disadvantages and because no consensus exists on which method is superior, it is surprising that no study using DEA has been conducted in the health systems research field. However, in hospital studies, DEA is the most frequently used approach to measure efficiency. In this study we use DEA due to its advantage of allowing for multiple inputs and outputs to be considered simultaneously. This seems particularly appropriate to measuring the efficiency of complex service organizations like hospitals. Moreover, DEA has the advantage of not requiring that any assumptions be made about the functional form of the production or cost frontier in contrast to parametric methods, such as SFA. Thus, there is no need for a theoretical exposition of the model [21, 22]. Third, the impact of health systems on hospital performance is only partially analyzed in prior health system research. Existing studies focus exclusively on one outcome variable of organizational performance, such as hospital profitability. Based on Fottler [23], a more adequate approach to comprehensively analyze performance may include two different determinants: efficiency (productivity and cost efficiency) and effectiveness (e.g., financial outcomes). In this study, we address the aforementioned limitations of the prior literature by conducting an interventional study based on hospital technical and cost efficiency and hospital profitability.

3 Estimation strategy

3.1 Data

This study is based on data from annual reports of all German hospitals from 2000 to 2011 that were collected and administered by the Research Data Center of the Federal Statistical Office of Germany [24]. The comprehensive dataset contains both hospital-level information on hospital costs and infrastructure and patient-level information on patient characteristics, such as age, medical diagnosis, or procedures for all public, private for-profit, and private non-profit hospitals in Germany (n=2,045). We exclude hospitals with the following characteristics to ensure the comparability of the data sample: hospitals with fewer than 50 and more than 2,000 beds, hospitals providing only psychiatric care, university hospitals, day clinics, and German army hospitals [22, 25, 26]. In contrast to the US, where the American Hospital Association (AHA) has collected information on health systems since the 1970s, in Germany, no information is publicly available to provide a comprehensive overview of German hospitals' health system membership [cf. 27]. Because of the lack of detailed information about health systems in this dataset, we collected further data on potential hospital affiliation with a health system and, if such an affiliation existed, the year that the hospital joined the health system from publicly available sources, such as websites and press releases. For the relevant study period from 2000 to 2011, we obtained information on all hospital entries into health systems. Hospitals that belonged to health systems with health system entry before 2000 were not taken into account (n=335). Ultimately, a total of 833 hospitals remained in the sample, including 399 that entered into health systems and 434 independent hospitals. Furthermore, we collected data on financial criteria that reflect hospital profitability for the period from 2008 to 2011 from publicly available annual financial reports and incorporated them into the dataset. We compared our obtained samples to the national sample of German hospitals and found most covariates to be quite similar. For instance, in the national German hospital market, approximately one-third of the hospitals are public, private for-profit or private non-profit. In the samples we use to analyze hospital efficiency and profitability, the distribution of hospital ownership is almost identical. However, with a mean of 343 and 341 beds per hospital, the hospitals in the efficiency and profitability samples are slightly larger than the general hospital population (mean=249 hospitals). Because the public availability of hospital financial reports is restricted, the sample used to analyze the effect of hospital entry on hospital profitability (around n=356 depending on the different financial indicators) is smaller than the sample used to analyze the effect of hospital entry on hospital efficiency (n=833).

3.2 Data envelopment analysis

DEA is a linear programming method that examines the relationship between several inputs (e.g., resources used or costs) and outputs (e.g., number of patients treated) of each hospital's production process from observed data and compares the result with the best practice frontier [28]. Thus, two cases can be distinguished: hospitals can minimize inputs for a given output (an input-oriented model) or maximize output given a fixed number of inputs (an output-oriented model). We assume that hospitals have an input orientation because hospital managers can control the number of hired staff or hospital costs, whereas the number of patients treated – i.e., the output – can be viewed as exogenous [22, 26, 29].

Charnes et al. [30] propose a DEA model under constant returns to scale (CRS). Subsequent research has used alternative sets of assumptions, such as Banker et al. (BCC) [31], who propose a variable returns to scale (VRS) model. The BCC approach is more flexible than the CRS approach [28] because it does not imply that all organizations necessarily operate at an optimal scale to be efficient [31]. Because the German health care sector can be characterized by market constraints, including imperfect competition, government regulation, and regulatory constraints on budgets, mergers, entries, and exits, we adopt the BCC approach with VRS and assume that hospitals operate at a non-optimal scale [32, 22]. Furthermore, we assume an intertemporal frontier and therefore merge the data for all years into one set and calculate technical and cost efficiency scores for the entire data set [33].

We correct the technical efficiency scores by bootstrapping because individual efficiency scores may not be robust in the presence of outlier observations and may be sensitive to the model specification and sampling variations [32, 34, 35, 7]. The bootstrapping procedure allows us to infer the statistical properties (confidence intervals, bias, and variance) of the estimated DEA efficiency scores [35]. In this study, bias-corrected technical efficiency scores are derived from 1,000 bootstrap iterations, which improves the statistical efficiency in the second-stage regression. DEA is performed by using R 2.14.2 [36] with the FEAR package [37].

For the analysis, the relevant inputs and outputs need to be selected. We thus follow other studies that have used DEA to measure hospital efficiency [e.g., 22, 32] and select the subsequent inputs and outputs for the measurement of technical and cost efficiency for hospitals in this study. As input variables, we choose the number of full-time equivalents (FTEs) for the following personnel categories: physicians, nurses, other clinical staff, administrative staff, and other non-clinical staff members. In doing so, we account for the relative importance of resource use in terms of labor in the hospital production process. Moreover, we choose the costs of medical supplies and the costs of other operating supplies as additional inputs to approximate material resources. The costs of other operating supplies represent the costs of total hospital supplies (costs of supplies per year excluding payroll, capital, and depreciation expenses) minus the costs of medical supplies.

Additionally, we include prices as input variables for the measurement of cost efficiency. The input price variables are used to adjust the input variables in DEA models estimating hospital cost efficiency [33]. As a result, we choose the prices of the aforementioned different personnel categories: physicians, nurses, other clinical staff, administrative staff, and other non-clinical staff members and the prices of medical and other supplies per bed. To assess the results for hospital technical and cost efficiency [cf. 32], we include beds as an additional fixed input and a proxy for capital input in a second DEA model specification. For hospital output, we use weighted inpatient cases. Thus, we follow the approach of Lindlbauer and Schreyögg [26] and construct the measure from patient-level information to ensure the comparability of case-mix resource intensity. Weights are based on length of stay, which is assumed to be a good proxy for severity of illness [cf. 38, 25]. In accordance with Dyson [39], we do not omit variables to increase discrimination, as this procedure is less effective with large data samples.

3.3 Genetic matching

A fundamental concern in health economic studies that use observational data is selection bias [40]. In other words, hospitals may differ not only with respect to belonging to a health system but also with respect to baseline characteristics such as size. This baseline imbalance may result in the over- or underestimation of the difference-in-difference effect attributed to entry into a health system [41]. For instance, if larger hospitals are more likely to enter into health systems and if larger hospitals have greater performance gains from entry than smaller hospitals, the results of the difference-in-difference approach will overestimate the effect of hospitals that enter into health systems if no baseline balance is created.

Hence, the key challenge is how to adjust for imbalances in baseline covariates. To resolve this problem, each hospital in a health system must be matched to its most similar independent (control) hospital on observable characteristics [42]. This can be achieved with different matching methods, which have become increasingly popular in many fields, including health economics. Two common approaches are univariate propensity score matching [43] and multivariate matching based on the Mahalanobis distance [44, 45]. However, there is no consensus on how matching should be performed and how to measure the success of matching procedures [8, 9].

In this study, we apply the relatively novel genetic matching approach to performing multivariate matching, which was first described by Sekhon and Mebane [46]. Genetic matching is a generalization of propensity score matching and Mahalanobis distance matching [9] and produces more accurate matches than other matching methods [e.g., 9]. Although there is strong support that genetic matching should be used in principle, the approach has been used by few researchers [47] and by almost none in the field of health economics [e.g., 48, 49, 8, 50].

The primary advantage of genetic matching is the use of an evolutionary search algorithm, which replaces the need to manually and iteratively check the covariate balance, as is the case when using propensity score matching. The actual matching is then performed by minimizing the multivariate distance between hospitals based on the weighted covariates, and this procedure is repeated until the best possible confounder balance in the overall sample is achieved (i.e., the group of independent control and of health systems hospitals have the same joint distribution of observed covariates) [9, 46].

Genetic matching is less sensitive to misspecifications of the model compared with univariate propensity score matching due to its multivariate characteristic [e.g., 50]. For technical details on genetic matching, please see Sekhon et al. [51].

In this study, we proceed in two steps to increase the similarity between the intervention group of health system hospitals and the control group of independent hospitals. In the first step, we perform a bootstrapped logistic regression by using defined covariates to derive propensity scores, i.e., the probability that each hospital will enter into a health system during the observation period. The covariates represent hospital and environmental characteristics, which may affect the likelihood of health system entry during the period observed. In particular, we control for hospital size, the proportion of all hospital beds, the proportion of leased hospital beds, and hospital performance prior to health system entry (based on the DEA technical and cost efficiency scores or the financial criteria, depending on the variable that is used in the final regression). As an environmental factor, we control for the Hirschman–Herfindahl index (HHI; market concentration with counties). The HHI is a standard economic measure of market concentration obtained by squaring a hospital's regional market share (reflected by the distribution of treated cases) and by subsequently summing the market share of admissions for all of the hospitals in a given county [cf. 22]. Finally, we include year dummies.

In the second step, genetic matching is performed by using the same variables as the individual covariates and the derived propensity scores. We thereby follow the advice of Diamond and Sekhon [9] and use the linear predictor of the propensity score estimated by logistic regression. As a result, each health system hospital in the intervention group is matched to one independent hospital in the control group in the corresponding baseline year – i.e., hospitals are matched based on their characteristics 1 year before health system entry. In all of the analyses in this study, we estimated the average treatment effect on the treated (ATT) by one-to-one matching with replacement, which implies that each independent hospital in the control group could be drawn more than once [cf. 9]. In this way, the total distance of matched pairs is minimized – i.e., optimal matching – resulting in the highest degree of balance in the observed variables and the lowest conditional bias [52]. Genetic matching is performed by using R 3.0.1 [36] with the MATCHING package [8].

3.4 Difference-in-difference

The use of matching estimators reduces the risk of selection bias, but only based on observables. An advantage of using a difference-in-difference approach is that unobserved, time-invariant, hospital-level effects and time effects between independent and health system hospitals are excluded from the estimation. Thus, a combined estimation strategy of matching and difference-in-difference regression is a suitable approach to obtain more accurate results [41].

In the regression analysis, we apply a fixed-effects truncated regression model with technical and cost efficiency scores as the dependent variable to analyze hospital efficiency attributable to the truncated distribution of DEA-based efficiency estimates [10]. To analyze hospital profitability, we apply a fixed-effect linear regression model for panel data. To measure hospital profitability, we follow Herr [25] and analyze the changes separately for earnings before interest and taxes (EBIT), earnings after taxes (EAT), return on investment (ROI), and operating margin [e.g., 2, 20]. EBIT and EAT are measured in absolute values, whereas ROI and the operating margin are ratios.

The difference-in-difference specification of the regression models is used to assess whether health system entry leads to improvements in hospital performance while controlling for patient heterogeneity, hospital organizational and environmental characteristics:

$$Y_{it} = X_0 + X_1 SYSTEM_i + X_2 POST_t + X_3 SYSTEM_i POST_t + X_4 Z_{it} + u_i + e_{it}$$

Y_{it} is defined as the performance (with the measures technical and cost efficiency, operating margin, ROI, EBIT, and EAT) of the ith hospital, $i=1, \ldots, N$, in year t, $t=1, \ldots., 12$. $SYSTEM_i$ is a dummy variable with a value of 1 if a hospital entered into a health system during the observation period between 2000 and 2011 and 0 for independent hospitals. This variable controls for time-invariant differences between health system hospitals in the intervention group and independent hospitals in the control group. $POST_t$ takes a value of 1 in the years after the hospital's entry into the system and 0 before (including the year of the entry) and thus controls for a common time trend. The coefficient of the interaction effect between $SYSTEM_i$ and $POST_t$ indicates potential changes in hospital performance after health system entry in relation to hospital performance in the control group and is thus the coefficient of focal interest. Z_{it} includes observable factors that affect the performance of hospital i in year t (beds, leased beds, and market concentration). u_i is the fixed effect, and the random term e_{it} is assumed to be normally distributed with zero mean. By conducting individual regressions for the different post-intervention periods, the serial correlation problem can be avoided [cf. 53]. We thereby distinguish four post-entry periods to measure the impact of health system entry on hospital technical and cost efficiency and use two post-entry periods to measure the impact of health system entry on hospital profitability owing to the shorter observation period of 2008 to 2011. In all cases, the pre-period is defined as the year before health system entry. Difference-in-difference methodology assumes that all other temporal factors affecting hospital performance have the same impact on independent and health system hospitals. Thus, we assume that any changes over time affect all hospitals in the sample similarly and do not control for these changes. Table 1 provides a comprehensive outline of the statistical analysis.

3.5 Sensitivity analyses

We check the robustness of the results in several ways: First, to assess the results for hospital technical and cost efficiency, we include only hospitals that cover the entire 4 years after entry. Second, to ensure the correctness of the results for hospital profitability, we use non-negative adjusted profits in the entire sample because profits may be negative. Third, health system entry might be associated with hospital privatization, which is defined as a conversion from public to private for-profit or private non-profit status [cf. 22]. Therefore, we control for potential privatization effects. Fourth, we estimate the results of hospital technical and cost efficiency and hospital profitability by using a reduced control group of only independent hospitals without any type of loose, non-formal cooperative arrangements. As a last sensitivity analysis, we increase the accuracy of the genetic matching and restrict the selection of pairs between independent and health system hospitals by using a caliper of 0.2 of the standard deviation of the propensity score. Through simulation, Austin [54] identifies this caliper width as the most appropriate.

4 Results

4.1 Descriptive results

A total of 864 hospitals remain in the data sample, including 399 hospitals that enter into health systems between 2000 and 2011. Table 2 summarizes the descriptive statistics for the

Table 1 Outline of the statistical analysis

Steps	Efficiency	Profitability
1. Increasing homogeneity of the sample	(1) Exclusion of hospitals with fewer than 50 beds and more than 2,000 beds, hospitals providing only psychiatric care, university hospitals, day clinics and German army hospitals	(1) Exclusion of hospitals with fewer than 50 beds and more than 2,000 beds, hospitals providing only psychiatric care, university hospitals, day clinics and German army hospitals
	(2) Hospitals that belonged to health systems with health system entry before 2000 were not taken into account	(2) Hospitals that belonged to health systems with health system entry before 2000 were not taken into account
2. Identification of intervention and control groups	Separation of intervention and control groups	Separation of intervention and control groups
3. Data Envelopment Analysis (DEA)	Application of an input-oriented VRS model. DEA is performed for all years 2000–2011. Bias-corrected DEA efficiency scores are derived from 1.000 bootstrapping iterations	
4. Genetic Matching (GM)	(1) Estimation probability of each hospital to enter in health system based on the defined covariates by means of logistic regression	(1) Estimation probability of each hospital to enter in health system based on the defined covariates by means of logistic regression
	(2) Match independent and health system hospitals by using a one-to-one matching with replacement without caliper	(2) Match independent and health system hospitals by using a one-to-one matching with replacement without caliper
5. Regression Analysis	Use of a fixed-effects truncated regression model data with DEA technical and cost efficiency scores as dependent variables	Use of a fixed-effects linear regression model with operating margin, ROI, EBIT and EAT as dependent variables
6. Sensitivity Analysis	(1) Re-estimation including only hospitals cover the entire four periods	(1) Re-estimation of profitability models using non-negative adjusted profits
	(2) Re-estimation with control for potential privatization effects in the analysis	(2) Re-estimation with control for potential privatization effects in the analysis
	(3) Re-estimation of the GM model by using only independent hospitals without any type of loose, non-formal cooperative arrangements as control group	(3) Re-estimation of the GM model by using only independent hospitals without any type of loose, non-formal cooperative arrangements as control group
	(4) Re-estimation of the GM model by employing a caliper of 0.2	(4) Re-estimation of the GM model by employing a caliper of 0.2

Table 2 Descriptive statistics and efficiency scores

Year	2000		2005		2011	
	Mean	SD	Mean	SD	Mean	SD
Independent hospitals						
n	396		429		434	
Cases (in 1,000)	10.5	8.5	11.3	9.0	13.0	10.3
Weighted cases (in 1,000)	10.0	8.0	10.8	8.5	12.4	9.7
Beds	347.9	261.0	343.1	255.7	342.8	266.3
Physician	64.6	67.3	74.5	74.6	88.4	86.3
Nurse	201.4	178.1	191.1	167.0	206.1	181.1
Clinical	118.9	123.1	123.1	124.2	139.6	135.5
Admin	31.4	26.5	33.1	28.0	36.6	30.6
Nonclinical	77.7	92.0	68.4	70.7	57.8	64.1
Cost for medical supplies (in 100 kEUR)	9.6	11.0	12.1	13.5	15.6	16.7
Cost for other operating supplies (in 100 kEUR)	2.0	2.6	1.6	3.2	2.4	4.4
Price for physician (in 1,000 EUR)	86.1	11.5	88.6	11.2	98.6	13.1
Price for nurse (in 1,000 EUR)	45.1	5.2	45.8	5.6	44.8	5.9
Price for clinical (in 1,000 EUR)	42.5	6.2	45.2	5.5	44.4	6.5
Price for admin (in 1,000 EUR)	46.1	8.9	48.9	10.6	49.2	9.8
Price for nonclinical (in 1,000 EUR)	34.7	16.0	33.7	9.8	37.8	22.4
Price for medical supplies per bed (in 1,000 EUR)	24.7	24.6	31.9	29.0	41.3	31.0
Price for other operating supplies per bed (in 1,000 EUR)	6.3	7.3	5.4	9.8	7.8	11.0
Technical efficiency scores	0.599	0.132	0.601	0.129	0.614	0.131
Cost efficiency scores	0.401	0.154	0.351	0.150	0.324	0.140
			2008		2011	
			Mean	SD	Mean	SD
n			210+		198+	
Operating margin			0.011	0.041	0.005	0.058
ROI			0.012	0.050	0.009	0.050
EBIT (in 1,000 EUR)			190.3	462.4	237.7	534.5
EAT (in 1,000 EUR)			199.9	538.0	237.9	503.9
Year	2000		2005		2011	
	Mean	SD	Mean	SD	Mean	SD
Health system hospitals						
n	418		432		416	
Cases (in 1,000)	9.4	6.7	10.0	7.5	11.7	8.8
Weighted cases (in 1,000)	9.0	6.2	9.6	7.0	11.1	8.2
Beds	300.6	204.9	296.5	205.7	293.8	212.3
Physician	53.5	52.9	63.2	63.2	75.6	73.0
Nurse	169.3	139.9	159.3	134.4	166.1	135.9
Clinical	96.9	92.6	102.2	99.1	116.3	108.1
Admin	28.3	23.1	28.3	24.1	28.1	26.1
Nonclinical	63.9	60.9	53.2	52.5	38.3	40.3
Cost for medical supplies (in 100 kEUR)	7.5	7.7	9.8	9.7	12.8	12.0
Cost for other operating supplies (in 100 kEUR)	2.1	2.7	1.9	3.0	2.9	4.0
Price for physician (in 1,000 EUR)	88.7	11.7	91.4	10.0	10.4	15.6
Price for nurse (in 1,000 EUR)	46.0	4.3	46.8	5.2	46.2	6.1
Price for clinical (in 1,000 EUR)	43.7	6.1	46.2	5.8	45.8	6.7
Price for admin (in 1,000 EUR)	44.6	7.9	48.5	12.2	51.3	24.7
Price for nonclinical (in 1,000 EUR)	34.4	8.6	34.9	11.1	44.1	48.8

Table 2 (continued)

Year	2000		2005		2011	
	Mean	SD	Mean	SD	Mean	SD
Price for medical supplies per bed (in 1,000 EUR)	22.5	13.9	29.9	14.7	40.5	19.7
Price for other operating supplies per bed (in 1,000 EUR)	6.9	5.1	7.0	6.9	10.4	10.2
Technical efficiency scores	0.601	0.110	0.605	0.114	0.638	0.118
Cost efficiency scores	0.410	0.132	0.335	0.127	0.320	0.135
			2008		2011	
			Mean	SD	Mean	SD
n			181^{+}		158^{+}	
Operating margin			0.002	0.086	0.010	0.060
ROI			0.010	0.065	0.015	0.083
EBIT (in 1,000 EUR)			93.2	427.6	152.8	490.9
EAT (in 1,000 EUR)			166.9	470.7	103.0	519.1

SD=Standard deviation, $^{+}$ Number of hospitals varies

different input and output variables that are used in the DEA and the technical and cost efficiency scores for the years 2000, 2005, and 2011 for the independent and health system hospital groups. Furthermore, the descriptive statistics for the hospital profitability variables are presented for 2008 and 2011.

4.2 Genetic matching results

The differences in the covariate means between independent and health system hospitals are smaller after than before the genetic matching. We generally observe an imbalance of baseline characteristics before the matching procedure. For instance, independent hospitals are, on average, larger than health system hospitals. After genetic matching, the differences in the covariate means between independent and health system hospitals are less than 0.7 % in the post-matching distribution for hospital efficiency and less than 5.3 % for hospital profitability (cf. Appendix Table 1). According to Austin and Mamdani [55] and Normand et al. [56], a standardized difference of less than 10 % represents a baseline balance between the intervention and control groups.

Logistic regressions provide the propensity score of each hospital entering into a health system. Our findings in Table 3 reveal that smaller hospitals are more likely to enter into health systems than larger hospitals ($p \leq 0.05$). Moreover, hospitals with a higher rate of leased beds are more likely to enter into health systems than hospitals with a lower rate of leased beds ($p \leq 0.1$).

These results are comparable to those for hospital cost efficiency and those for the various models for hospital profitability. In addition, less cost efficient hospitals and hospitals with a lower EBIT are more likely to enter into health systems than other hospitals (at least $p \leq 0.1$).

4.3 Difference-in-difference regression results

The following tables show the regression results for changes in hospital performance. The coefficients of the difference-in-difference interaction between the variables SYSTEM and POST are presented. The interaction terms identify changes in hospital performance after health system entry relative to the corresponding changes in the control group of independent hospitals. The results are based on the matched samples after genetic matching. Table 4 summarizes the regression results for changes in hospital technical and cost efficiency after genetic matching for the four post-intervention periods, with the DEA technical and cost efficiency scores as dependent variables in the regressions (models I-IV).

The net effect of health system entry increases with the number of years since entry. The values of the coefficients are slightly higher for technical efficiency than for cost efficiency. In model I, all difference-in-difference coefficients are positive and significant (at least at a level of $p \leq 0.05$). We find a significant increase of 0.8 % ($p \leq 0.01$) in technical efficiency for hospitals in health systems relative to independent hospitals in the year of entry and an increase of 1.7 % ($p \leq 0.001$) in the first year after entry. The efficiency gains are slightly smaller in the second year after entry (1.1 %, $p \leq 0.05$). In the third and fourth year after entry, we observe an increase of 2.0 and 3.4 % ($p \leq 0.001$), respectively, in technical efficiency. These results indicate that the positive effect of entering into a health system is not transitory but rather permanent. To ensure that variations in the difference-in-difference estimates are not due to differences in the samples, we conduct an additional analysis based on a second DEA model that includes beds as an additional fixed input (model II). Again, all difference-in-difference coefficients are significant (at least at

Table 3 Results of logistic regressions on health system entry

Technical efficiency				Cost efficiency			
Health system entry				Health system entry			
Intercept	17.900		(904.200)	Intercept	−2,702	****	(0.277)
Beds	−0.001	**	(0.003)	Beds	−0.001	**	(0.000)
Leased beds	1.003	*	(0.402)	Leased beds	0.746	**	(0.346)
Market concentration	−0.003		(0.453)	Market concentration	0.461		(0.381)
Technical efficiency	−0.151		(0.542)	Cost efficiency	−0.650	*	(0.415)
Year 2000	(*Reference*)			Year 2000	(*Reference*)		
Year 2001	−0.042		(1180.000)	Year 2001	0.310		(0.308)
Year 2002	0.026		(1180.000)	Year 2002	0.268		(0.308)
Year 2003	−0.061		(1085.000)	Year 2003	0.722	**	(0.285)
Year 2004	−19.230		(904.200)	Year 2004	1,355	****	(0.265)
Year 2005	−19.720		(904.200)	Year 2005	0.857	***	(0.279)
Year 2006	−20.170		(904.200)	Year 2006	0.404		(0.298)
Year 2007	−19.720		(904.200)	Year 2007	0.853	***	(0.278)
Year 2008	−20.060		(904.200)	Year 2008	0.501	*	(0.292)
Year 2009	−20.300		(904.200)	Year 2009	0.261		(0.306)
Profitability							
Health System Entry				Health System Entry			
Intercept	−1.796	****	(0.469)	Intercept	−2.324	****	(0.645)
Beds	−0.003	**	(0.001)	Beds	−0.001		(0.002)
Leased beds	−0.716		(1.903)	Leased beds	−3.586		(5.431)
Market concentration	0.204		(1.376)	Market concentration	−0.437		(2.295)
Operating Margin	−0.974		(0.407)	EBIT	−0.000	**	(0.000)
Year 2008	(*Reference*)			Year 2008	(*Reference*)		
Year 2009	−0.064		(0.389)	Year 2009	−0.219		(0.585)
Health System Entry				Health System Entry			
Intercept	−2.142	****	(0.477)	Intercept	−2.185	****	(0.563)
Beds	−0.002	*	(0.001)	Beds	−0.002		(0.002)
Leased beds	−0.263		(1.702)	Leased beds	−3.208		(4.133)
Market concentration	−0.021		(1.538)	Market concentration	0.938		(1.766)
ROI	−4.520		(3.464)	EAT	−0.000		(0.000)
Year 2008	(*Reference*)			Year 2008	(*Reference*)		
Year 2009	0.110		(0.405)	Year 2009	−0.302		(0.502)

* $p<0.1$, ** $p<0.05$, *** $p<0.01$, **** $p<0.001$; standard error (SE) in parentheses

a level of $p\leq0.05$). In general, both models yield comparable results for hospital efficiency. Until 2 years after hospital entry, we observe an increase in technical efficiency of 0.6 % ($p\leq0.05$) in the year of entry and an increase of 2.0 % ($p\leq0.001$) in the first year after entry in model II. We again observe a slight decrease in efficiency gains of 1.1 % ($p\leq0.01$) in the second year after entry. Three and four years after entry, the efficiency gains again increase to 2.1 and 3.4 % ($p\leq0.001$), respectively.

In general, the findings for cost efficiency confirm the trend of an increase of hospital efficiency throughout the observation period of four intervention periods (model III). At least 2 years after health system entry, we find a significant increase in cost efficiency of 1.0 % for hospitals in health systems relative to independent hospitals ($p\leq0.05$). The efficiency gains are slightly smaller in the third year after entry (0.8 %, $p\leq0.1$). Four years after entry, we observe a significant increase in cost efficiency of 1.3 % ($p\leq0.05$). In model IV, which includes beds within a second DEA model specification, we again observe no significant effects prior to the second year. However, comparable to the results for model III, the results show that health system entry raises hospital cost efficiency by 1.0 % ($p\leq0.05$) in the second year after entry. In the third year after entry, the efficiency gains are slightly smaller at 0.8 % ($p\leq0.1$). Four years after entry, we observe a significant increase in cost efficiency of 1.5 % ($p\leq0.01$).

Table 4 Effects of health system entry on hospital efficiency (difference-in-difference coefficients)

Period	t		t+1		t+2		t+3		t+4	
n	1586⁺		1570⁺		1436⁺		1304⁺		1096⁺	
Model I: *technical efficiency*										
SYSTEM*POST	0.008	***	0.017	****	0.011	**	0.020	****	0.034	****
	(0.003)		(0.004)		(0.004)		(0.005)		(0.006)	
Model II: *technical efficiency - including beds*										
SYSTEM*POST	0.006	**	0.020	****	0.011	***	0.021	****	0.034	****
	(0.003)		(0.003)		(0.004)		(0.005)		(0.006)	
Model III: *cost efficiency*										
SYSTEM*POST	0.002		0.005		0.010	**	0.008	*	0.013	**
	(0.003)		(0.004)		(0.004)		(0.005)		(0.006)	
Model IV: *cost efficiency - including beds*										
SYSTEM*POST	0.002		0.002		0.010	**	0.008	*	0.015	***
	(0.003)		(0.003)		(0.004)		(0.005)		(0.006)	

* $p<0.1$, ** $p<0.05$, ***$p<0.01$, **** $p<0.001$; SE in parentheses; ⁺ Number of hospitals varies

Table 5 presents the results for changes in hospital profitability, as measured with operating margin, ROI, EAT, and EBIT, for two post-intervention periods (models I-IV). Using the matched samples, we find a significant increase in hospital profitability compared to the control group 1 year after health system entry in all the estimation models ($p\leq0.05$ or $p\leq0.1$). The ratio-based indicators operating margin and ROI reveal an increase of 2.6 % (operating margin) and 3.5 % (ROI) in hospital profitability 1 year after entry for hospitals in health systems relative to independent hospitals. Moreover, for the absolute measures, EBIT and EAT show growth of 825,786 and 607,708 Euros, respectively, in hospital profitability for hospitals in health systems relative to independent hospitals. These results reveal a transitory rather than a permanent effect of health system entry on hospital profitability.

4.4 Sensitivity analyses results

A range of sensitivity analyses reveal that the findings are robust to various changes in the model assumptions and methods. First, we employ a reduced model that includes only hospitals that cover the entire 4 years for hospital technical and cost efficiency (cf. Table 4, 548 hospitals). This model shows comparable gains in hospital efficiency throughout the observation period. The coefficients of technical efficiency are slightly higher in the year of entry, the second year after entry, and the third year after entry; the coefficients of cost efficiency are higher in all years except in the fourth year after entry. The significance levels for both estimation models are mostly comparable to those from the main analysis. Second, we rerun the analysis of hospital profitability and use exclusively non-

Table 5 Effects of health system entry on hospital profitability (difference-in-difference coefficients)

Period	t	t+1		t+2
n	100⁺	82⁺		46⁺
Model I: *Operating margin*				
SYSTEM*POST	−0.002	0.026	*	0.036
	(0.018)	(0.014)		(0.022)
Model II: *ROI*				
SYSTEM*POST	0.015	0.035	*	0.016
	(0.016)	(0.019)		(0.016)
Model III: *EBIT*				
SYSTEM*POST	300,140	825.786	*	−107,527
	(224,880)	(392,427)		(311,968)
Model IV: *EAT*				
SYSTEM*POST	246,507	607.708	**	−112,155
	(257,680)	(206,724)		(385,502)

* $p<0.1$, ** $p<0.05$; SE in parentheses; ⁺ Number of hospitals varies

negative values for profits. The significant increase in hospital profitability in the first year after health system entry is confirmed. However, the coefficients are slightly lower than those in the main analysis. Third, to control for potential privatization effects, hospitals that simultaneously entered into a health system and converted from public to private for-profit or private non-profit hospital status are excluded. The results for hospital technical and cost efficiency are confirmed. The significance levels for both estimations are mostly comparable to those from the main analysis. Fourth, using a reduced control group consisting of only independent hospitals, we confirm the hospital performance gains of health system entry. The results reveal only minor changes in the difference-in-difference coefficients and their significance levels for hospital technical and cost efficiency and hospital profitability. Finally, we use a caliper of 0.2 of the standard deviation of the propensity score to increase the accuracy of the genetic matching. The coefficients of the interaction effect have the same direction throughout the observation period, and the significance levels for hospital technical, cost efficiency, and hospital profitability are comparable to those from the main analysis.

5 Discussion

Based on resource dependence theory, we assume that hospitals only enter into multi-institutional arrangements when they anticipate that the relationship will benefit them [57]. The transaction cost theory suggests that hospitals within health systems can reduce the costs of monitoring and coordinating and thus enhance hospital efficiency. Prior research has identified the potential benefits of health systems such as cost savings and efficiency gains by reducing duplicative equipment or administrative functions. Moreover, health systems are assumed to provide benefits such as shared information and resources, easier access to capital and services, and bargaining power [3, 58]. Our results support the theoretical postulations and empirical findings described above, as we detect an increase in hospital efficiency after health system entry throughout the observation period.

From the transaction cost perspective, entry is always associated with additional cost in the short term that results from increased complexity when two or more hospitals decide to cooperate [cf. 59]. Several authors have identified the disadvantages of hospital membership in health systems in the short term. For instance, the internal restructuring of health systems-associated bureaucracy may temporarily reduce hospital efficiency. Health system entry may also require new investments in management operations and infrastructure. Additionally, hospitals will unavoidably lose their operating autonomy and control. Multi-institutional arrangements may initially increase the costs of communication among hospitals and delay decision making. Thus, losses in hospital efficiency may be particularly possible in the short term [19, 57]. Our study does not provide any evidence of efficiency losses; however, the mentioned disadvantages might explain why hospital efficiency gains increase over time.

Health system hospitals, compared to independent hospitals, may be able to obtain lower prices for their inputs because of the large size of purchased inputs in health systems or imperfect competition in the hospital market. Based on the transaction cost theory, one underlying determinant for hospitals that enter in health systems is thus to operate more cost efficiently. Hospitals that are more experienced in these multi-institutional arrangements through prior participation are more likely to appreciate the aforementioned benefits and to promote further cooperation. Long-lasting interaction leads to trust among involved hospitals, which then helps limit the costs associated with future collaboration. Thus, trust in conjunction with a positive past experience leads to greater performance gains [19, 60].

According to resource dependence theory, health system managers are presumed to be capable of making choices. These choices will enable them to enhance their power and effectiveness and reduce competitive uncertainty [e.g., 13, 3]. Our results reveal that a hospital's entry into a health system has a positive impact on the hospital's profitability but that this effect is only significant 1 year after entry. The positive relationship between health system membership and hospital profitability confirms findings from numerous previous studies [19]. However, other studies, such as Dranove et al. [58], suggest that the potential financial benefits of health system membership may be overrated. Bureaucracy may increase production and distribution inefficiency, and a loss of flexibility may diminish a hospital's ability to respond to market conditions [cf. 19]. Tennyson and Fottler [20] find little evidence of enhanced hospital profitability from health system membership and conclude that hospitals enter into health systems to gain legitimacy and consistency with institutional norms rather than to enhance their profitability. Our findings provide stronger support for hospital efficiency gains than for profitability gains for health system entry. However, some temporary profitability effects from health system entry can be expected.

6 Conclusion

This study investigates the post-intervention effects of health system entry on hospital performance in Germany. We find that the increase in hospital efficiency after health system entry does not appear to be a transitional phenomenon. The results are similar for cost efficiency and technical efficiency. Regarding hospital profitability, the results reveal an increase in hospital profitability only 1 year after a hospital's entry into a health system. The estimations suggest that this effect is transitory.

This investigation has several strengths compared to previous studies analyzing hospital health systems. First, to our knowledge, this is the first study to examine the potential effects of health systems within an intervention study and to investigate changes in hospital performance after health system entry by using a panel data approach. Second, in health systems research, we are the first to employ a two-stage approach combining DEA with a novel matching method – genetic matching – and a difference-in-difference regression to control for possible bias in the analysis of hospital efficiency. In doing so, we also contribute to the literature from a methodological point of view. Third, this study is the first to analyze the impact of a hospital's entry into a health system on both hospital efficiency and hospital profitability as measures of hospital performance. Fourth, we obtain a unique, large data sample of German health systems through extensive data collection. Finally, this study is based on a large data sample that contains numerous environmental and organizational characteristics of all German hospitals for the period from 2000 to 2011 to appropriately control for both determinants of hospital performance and the impact of health system entry.

Although this study contributes to the existing literature in several ways, it also has important limitations. First, this study exclusively focuses on hospital health systems because of the restricted availability of public information about health networks. Further analysis including health networks would allow for a more comprehensive overview of multi-institutional arrangements in the hospital sector. Second, the analysis of changes in hospital profitability is based on limited data for the period from 2008 to 2011, which only provides evidence for the short term. One should consider this limitation when drawing implications regarding hospital profitability. Third, the data collection of financial criteria is restricted by the public availability of hospital financial reports. Due to the regulations of the Research Data Center, we are not allowed to merge information that is not publicly available. Moreover, a large number of health system hospitals publish financial criteria at the system level only, excluding the hospital level. Thus, the observable number of hospitals in the analysis of hospital profitability is diminished. Fourth, the financial criteria that we use to measure hospital profitability are not appropriate for all types of hospital ownership. For instance, public hospitals are not allowed to distribute profits and thus enter EAT as zero in their financial reports. A more detailed analysis of hospital profitability that considers the potential effects of hospital ownership would help to refine this study's findings. However, the small sample size limits our ability to investigate these effects. Fifth, we also tried to include a system member-fixed effect in addition to a time-fixed effect to consider the differences in behavior among health systems. However, such inclusion led to an over-specification of our model results, as there is a large number of health systems in our sample. Our exploratory descriptive analyses suggest that there are certain differences among health systems, but the majority of health systems generated quite similar efficiency gains, which is also reflected by the low variance of our regression results shown in Table 4. Finally, changes in the quality of hospital care after health system entry are of great interest but are not considered in this study. Until now, relatively few studies, such as Chukmaitov et al. [61] and Madison [62], have focused on the impact of hospital health systems on hospital quality. Again, data limitations hinder our ability to examine the potential relationship between health system entry and quality of care.

This study has several implications for management, policy, and research. From a management perspective, the study findings provide new insight into the understanding of the relationship between health system participation by hospitals and hospital performance. Therefore, the findings from this study should deepen the discussion about hospital health systems. In general, health system entry could be an appropriate management instrument for decision makers to increase hospital performance. When making decisions about health system entry, hospital managers should base their decisions on hospital efficiency rather than on hospital profitability. From a policy perspective, the results of this study support a recommendation of health system entry to achieve higher efficiency in the hospital sector. In addition to its practical relevance, this study has also various implications for further research. The analysis of hospital profitability is based on only two post-intervention periods. Thus, the observed increase in hospital profitability after health system entry may be transitory. However, health system entry may still lead to higher hospital profitability over longer periods than those studied here. Thus, future studies should include a longer period to explore further potential effects on hospital profitability over the long term. This study uses several financial criteria to investigate the impact of health system entry on hospital profitability. Although hospital profitability represents an aspect of financial performance, it does not cover other important aspects of financial performance, such as hospital liquidity. Therefore, future research should extend our findings and explain changes in hospital financial performance by using financial criteria such as liquidity ratios. This study focuses on the impact of health system entry on hospital performance; however, potential changes in employment effects after health system entry are not analyzed and should be analyzed in more detail in future studies.

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Appendix Table 1. Balance in measured covariates before and after matching

Group	Unmatchend sample Intervention (n=399)	Matched sample Control (n=465)	di (%)	Intervention (n=399)	Control (n=399)	di (%)
Mean	Mean		Mean	Mean		
Weighted cases (in 1,000)	9.7	11.3	6.4	9.7	9.5	1.6
Beds	297.5	340.8	4.9	297.5	292.4	1.1
Leased beds	0.071	0.051	9.3	0.071	0.071	0.9
Market concentration	0.196	0.200	2.4	0.197	0.193	1.2
Technical efficiency	0.598	0.604	3.7	0.598	0.598	0.7
Cost efficiency	0.338	0.360	2.8	0.320	0.321	0.6
Operating margin	0.013	0.015	11.9	0.013	0.016	5.3
ROI	0.007	0.019	3.2	0.007	0.009	1.7
EBIT	−56,711	243.282	20.2	−56,711	−56,469	4.0
EAT	75.463	239.331	8.5	75.463	78.281	4.7

Number of hospitals varies across the different models

References

1. Rosko MD, Proenca J, Zinn JS, Bazzoli GJ (2007) Hospital inefficiency: what is the impact of membership in different types of systems? Inquiry 44:335–349
2. Nauenberg E (1999) Network structure and hospital financial performance in New York State: 1991–1995. Med Care 56(4):415–439. doi:10.1177/107755879905600402
3. Oliver C (1990) Determinants of interorganizational relationships: integration and future directions. Acad Manag Rev 15:241–265
4. Rosko MD, Proenca J (2005) Impact of network and system use on hospital X-inefficiency. Health Care Manag Rev 30:69–79
5. Bazzoli GJ, Shortell SM, Dubbs N, Chan C, Kralovec P (1999) A taxonomy of health networks and systems: bringing order out of chaos. Health Serv Res 33:1683–1717
6. Shortell SM, Bazzoli GJ, Dubbs NL, Kralovec P (2000) Classifying health networks and systems: managerial and policy implications. Health Care Manag Rev 25:9–17
7. Simar L, Wilson PW (2000) A general methodology for bootstrapping in non-parametric frontier models. J Appl Stat 27:779–802. doi:10.1080/02664760050081951
8. Sekhon JS (2011) Multivariate and propensity score matching software with automated balance optimization: the matching package for R. J Stat Softw 42:1–52
9. Diamond A, Sekhon JS (2013) Genetic matching for estimating causal effects: a general multivariate matching method for achieving balance in observational studies. Rev Econ Stat 95:932–945. doi:10.1162/REST_a_00318
10. Simar L, Wilson PW (2007) Estimation and inference in two-stage, semi-parametric models of production processes. J Econom 136:31–64. doi:10.1016/j.jeconom.2005.07.009
11. Herwartz H, Strumann C (2012) On the effect of prospective payment on local hospital competition in Germany. Health Care Manag Sci 15:48–62. doi:10.1007/s10729-011-9180-9
12. Williamson OE (1985) The economic institutions of capitalism: firms, markets, relational contracting. Free Press, New York
13. Pfeffer J, Salancik GR (1978) The external control of organizations. New York
14. Williamson OE (1991) Comparative economic organization: the analysis of discrete structural alternatives. Adm Sci Q 36:269–296. doi:10.2307/2393356
15. Shortell S, Bazzoli GJ, Dubbs N, Kravolec P (2000) Classifying Health Networks and Systems: Managerial and Policy Implications. 25 (4):9–17
16. Alexander JA, Lee S-YD, Bazzoli GJ (2003) Governance Forms in Health Systems and Health Networks. 28 (3):228–242
17. Carey K (2003) Hospital cost efficiency and system membership. Inquiry 40:25–38
18. Proenca EJ, Rosko MD, Dismuke CE (2005) Service collaboration and hospital cost performance: direct and moderating effects. Med Care 43:1250–1258. doi:10.2307/3768212
19. Bazzoli GJ, Chan B, Shortell SM, D'Aunno TA (2000) The financial performance of hospitals belonging to health networks and systems. Inquiry 37:234–252
20. Tennyson DH, Fottler MD (2000) Does system membership enhance financial performance in hospitals? Med Care Res Rev 57:29–50
21. Hollingsworth B (2008) The measurement of efficiency and productivity of health care delivery. Health Econ 17:1107–1128. doi:10.1002/hec.1391
22. Tiemann O, Schreyögg J (2012) Changes in hospital efficiency after privatization. Health Care Manag Sci 15:310–326. doi:10.1007/s10729-012-9193-z
23. Fottler M (1987) Health care organizational performance: present and future research. JMS 13:367–391
24. Federal Statistical Office of Germany (2013) Krankenhausstatistik (Teil I: Grunddaten, Teil II: Diagnosen und Teil III: Kostennachweis) der Jahre 2000–2011, Antrag 2216–2013
25. Herr A, Schmitz H, Augurzky B (2011) Profit efficiency and ownership of German hospitals. Health Econ 20:660–674. doi:10.1002/hec.1622
26. Lindlbauer I, Schreyögg J (2014) The relationship between hospital specialization and hospital efficiency: Do different measures of

specialization lead to different results? Health Care Manag Sci online published first. doi:10.1007/s10729-014-9275-1
27. Schmid A, Ulrich V (2013) Consolidation and concentration in the German hospital market: the two sides of the coin. Health Policy 109: 301–310. doi:10.1016/j.healthpol.2012.08.012
28. Jacobs R (2001) Alternative methods to examine hospital efficiency: data envelopment analysis and stochastic frontier analysis. Health Care Manag Sci 4:103–115
29. Rego G, Nunes R, Costa J (2010) The challenge of corporatisation: the experience of Portuguese public hospitals. 11 (4):367–381. doi: 10.1007/s10198-009-0198-6
30. Charnes A, Cooper W, Rhodes E (1978) Measuring the efficency of decision making units. Eur J Oper Res 6:89–107
31. Banker R, Charnes A, Cooper W (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manag Sci 30:1078–1092. doi:10.1287/mnsc.30.9.1078
32. Jacobs R, Smith P, Street A (2006) Measuring efficiency in health care: analytic techniques and health policy. Cambridge University Press, Cambridge
33. Linna M (1998) Measuring hospital cost efficiency with panel data models. Health Econ 7:415–427. doi:10.1002/(SICI)1099-1050(199808)7:5<415::AID-HEC357>3.0.CO;2-9
34. Smith PC (1997) Model misspecification in data envelopment analysis. Ann Oper Res 73:233–252. doi:10.1023/A:1018981212364
35. Simar L, Wilson PW (1998) Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. Manag Sci 44: 49–61. doi:10.1287/mnsc.44.1.49
36. Team RDC (2013) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna
37. Wilson P (2008) FEAR: a software package for frontier efficiency analysis with R. Socio Econ Plan Sci 42:247–254. doi:10.1016/j.seps.2007.02.001
38. Herr A (2008) Cost and technical efficiency of German hospitals: does ownership matter? Health Econ 17:1057–1071. doi:10.1002/hec.1622
39. Dyson RG, Allen R, Camanho AS, Podinovski VV, Sarrico CS, Shale EA (2001) Pitfalls and protocols in DEA. Eur J Oper Res 132:245–259. doi:10.1016/S0377-2217(00)00149-1
40. Jones AM (2007) Identification of treatment effects in Health Economics. 16 (11):1127–1131. doi:10.1002/hec.1302
41. Blundell R, Dias M (2000) Evaluation methods for nonexperimental data. Fiscal Stud 21:427–468. doi:10.1111/j.1475-5890.2000.tb00031.x
42. Rubin DB (2007) The design versus the analysis of observational studies for causal effects: parallels with the design of randomized trials. Stat Med 2007 26(1):20–36. doi:10.1002/sim.2739
43. Rosenbaum P, Rubin D (1985) Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. ASA 39:33–38. doi:10.1080/00031305.1985.10479383
44. Rubin D (1979) Using Multivariate Sampling and Regression Adjustment to Control Bias in Observational Studies. 74:318–328
45. Rubin D (1980) Bias Reduction Using Mahalanobis-Metric Matching. 36 (2):293–298
46. Mebane WRJ, Sekhon JS (1998) R-GENetic optimization using derivatives (RGENOUD). Accessed 2014/04/21
47. Morgan S, Harding D (2006) Matching estimators of causal effects: prospects and pitfalls in theory and practice. SMR 35:3–60. doi:10.1177/0049124106289164
48. Frey S, Stargardt T (2012) Performance of compliance and persistence measures in predicting clinical and economic outcomes using administrative data from German sickness funds. Pharmacotherapy 32:880–889. doi:10.1002/j.1875-9114.2012.01120
49. Ramsahai R, Grieve R, Sekhon JS (2011) Extending iterative matching methods: an approach to improving covariate balance that allows prioritisation. Health Serv Outcomes Res Method 11:95–114. doi:10.1007/s10742-011-0075-5
50. Sekhon JS, Grieve R (2008) A new non-parametric matching method for bias adjustment with applications to economic evaluations
51. Sekhon JS, Grieve R (2012) A matching method for improving covariate balance in cost-effectiveness analysis. Health Econ 21: 695–714. doi:10.1002/hec.1748
52. Abadie A, Imbens G (2006) Large sample properties of matching estimators for average treatment effects. Econometrica 74:235–267. doi:10.1111/j.1468-0262.2006.00655.x
53. Bertrand M, Duflo E, Mullainathan S (2004) How much should we trust differences-in-differences estimates? QJE 119:249–275. doi:10.1162/003355304772839588
54. Austin P (2009) Some methods of propensity-score matching had superior performance to others: results of an empirical investigation and Monte Carlo simulations. Biom J 51:171–184. doi:10.1002/bimj.200810488
55. Austin P, Mamdani M (2006) A comparison of propensity score methods: a case-study estimating the effectiveness of post-AMI statin use. Stat Med 25:2084–2106. doi:10.1002/sim.2328
56. Normand S, Landrum M, Guadagnoli E, Ayanian J, Ryan T, Cleary P, McNeil B (2001) Validating recommendations for coronary angiography following an acute myocardial infarction in the elderly: a matched analysis using propensity scores. J Clin Epidemiol 54: 387–398. doi:10.1016/S0895-4356(00)00321-8
57. Provan KG (1984) Interorganizational cooperation and decision making autonomy in a consortium multihospital system. Acad Manag Rev 9:494–504. doi:10.2307/258289
58. Dranove D, Durkac A, Shanley M (1996) Are multihospital systems more efficient? Health Aff 15:100–104. doi:10.1377/hlthaff.15.1.100
59. Williamson OE (1975) Markets and hierarchies: a study in the internal organizations: analysis and antitrust implications. Free Press, New York
60. Wilcox-Gök V (2002) The effects of for-profit status and system membership on the financial performance of hospitals. Appl Econ 34:479–489. doi:10.1080/00036840110044180
61. Chukmaitov AS, Bazzoli GJ, Harless DW, Hurley RE, Devers KJ, Zhao M (2009) Variations in inpatient mortality among hospitals in different system types, 1995 to 2000. Med Care 47:466–473. doi:10.1097/MLR.0b013e31818dcdf0
62. Madison K (2004) Multihospital system membership and patient treatments, expenditures, and outcomes. Health Serv Res 39:749–769