The effects of strategic hospital alliances on hospital efficiency
Hsuan-Lien Chu and Chia-Yu Chiang*

Department of Accountancy, College of Business, National Taipei University, Taipei, Taiwan
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This study examines the effects of strategic alliances on the efficiency of hospitals controlled by the Department of Health in Taiwan. Overall, it is found that the efficiency of the hospitals improved after they formed strategic hospital alliances (SHAs). The results also indicate that smaller hospitals located in competitive areas are more efficient, as exemplified by shorter patient stays, higher occupancy rates, and lower mortality rates. Based on Taiwan’s experience, it is inferred that SHAs do improve the performance of the participating hospitals. It is hoped that the results of this study will encourage health policy officials and healthcare organizations in other countries to consider implementing similar strategies for their hospitals.

Keywords: strategic alliance; efficiency; hospital

Introduction
The National Health Insurance (NHI) scheme was established to increase the level of care for socially and economically disadvantaged people, and to improve the administrative efficiency and quality of healthcare services in Taiwan. Since the inception of the scheme in March 1995, healthcare expenditure has risen sharply each year due to the financial structure and the payment system of NHI. This trend was especially noticeable in 2006, when the cost of healthcare services grew by 10.61%, compared with an increase of 1.2% in the gross national product for the same year. Thus, controlling the growth of healthcare expenditure is an important aspect of government policy. In view of this, the Bureau of National Health Insurance recently implemented a cost reduction scheme in an attempt to stem the rising medical costs and nurture a cost-conscious culture in medical institutions.

Because of the increasing pressure from the NHI program, the need to cut costs has become more critical. In Taiwan, public hospitals are subject to higher administration and labor costs than private hospitals, but they have smaller budgets; hence, they face more financial pressures than private institutions. To address these problems, public hospitals must search for effective operating strategies to improve their performance.

One of the most popular operating strategies is called the strategic hospital alliance (SHA), whereby three or more hospitals with poor resources combine their procurement operations to achieve long-term goals, which would not be possible by one hospital operating independently. The purpose of an SHA is twofold: (1) to add value to each participating hospital and (2) to reduce costs through a centralized procurement mechanism. This
study examines the effects of forming strategic alliances on the efficiency of hospitals controlled by the Department of Health (DOH) in Taiwan.

We collected data from general hospitals controlled by the DOH, for the period 2001–2006. First, we utilized the data envelopment analysis (DEA) model to measure the technical efficiency of each hospital. Then, following prior studies (Ancarani, Di Mauro, & Giammanco, 2009; Brown & Pagán, 2006; Chen, Hwang, & Shao, 2005; Chu, Liu, & Romeis, 2004; Lee, Yang, & Choi, 2009), we used Tobit regression analysis to assess the effects of joining an SHA on a hospital’s efficiency. The objective was to control for other factors (e.g. the size of the hospital, the degree of competition, and the quality of patient care) that may also affect a hospital’s performance.

The remainder of this paper is organized as follows. The second section contains a review of related works. In the third section, we describe the research methodology and present our results, and finally, we summarize our conclusions.

**Literature review**

*Strategic alliances and hospitals*

When organizations are confronted by uncertainty, complex problems, and changes in their operating environments, alliances offer opportunities to pool resources and share risks to address such challenges. Today, hospitals are facing increasing pressure due to the shortage of financial and other resources; however, alliances between hospitals can strengthen each participant’s position by eliminating duplicate services and improving patient care. Hence, strategic alliances represent a rapidly growing phenomenon in the healthcare industry as in other industries.

Strategic alliances between hospitals have several potential benefits. For example, they reward efficient healthcare providers and achieve economies of scale through socially optimal combinations of price and quality (Baker, 2001; Clement et al., 1997; Dranove, Simon, & White, 2002). Moreover, hospitals may gain access to additional resources through collective purchasing and shared staffing arrangements (Halverson, Kaluzny, & Young, 1997). A number of studies (Plochg, Delnoij, & Klazinga, 2006; Williamson, 1981) have emphasized the advantages of SHAs, which differ from mergers in that the member hospitals retain their decision making powers. Moreover, the hospitals can reduce costs and improve medical technology through information exchange (Plochg et al., 2006; Wang, Wan, Burke, Bazzoli, & Lin, 2005). Chiang (2005) evaluated the effectiveness and progress of a regional health alliance in Taiwan one year after its establishment. The results indicate that the membership of the alliance improved the revenues and efficiency of the participating hospitals.

However, some studies claimed that economies of scale do not flow automatically from the size of hospitals and mergers. Recent studies have found that economies are achieved at low levels rather than at high levels of hospital scale, with more modest cost savings (Burns & Pauly, 2002). Consequently, strategic alliances may not improve efficiency through economies of scale. In addition, strategic alliances may incur new costs that result from inter-organizational cooperation, and hospitals that share medical techniques and resources with other providers may lose their technical superiority. Therefore, loss of autonomy and control may be unavoidable in inter-organizational alliances (Halverson et al., 1997; Zuckerman, 2006). Finally, alliances may increase the costs of communications between hospitals and delay decision making (Halverson et al., 1997).
Strategic alliances between hospitals in Taiwan

Many public hospitals in Taiwan face financial difficulties because of budgetary limitations and the strict requirements of the NHI scheme. To address the problem, the DOH adopted the concept of an integrated healthcare system and established SHAs among 29 hospitals controlled by the DOH in 2004. Currently, the alliances comprise 22 general hospitals (including branch hospitals), 1 specialized hospital, 5 convalescent hospitals, and 1 chest hospital. As a result, the hospitals have become more competitive and efficient because they have better control over operating costs in a number of areas, such as group purchasing, resource sharing, technical exchanges, joint marketing, and electronic commerce.

When the SHAs were set up in 2004, the participating hospitals were divided into four leagues: the Taipei league, the Northern league (which included the Eastern league), the Central league, and the Southern league. Each league selected a large general hospital as the operations and management hub, and the other hospitals in the alliance were affiliated with it. The central hospital integrates the medical resources and health insurance applications of its affiliates. For administrative reasons, in 2005, the DOH combined the Taipei league and the Northern league (including the Eastern league) to form the Northern regional league. Then, in 2007, the other two leagues were combined to form the Central and Southern regional leagues. Although hospitals can take advantage of strategic alliances to reduce costs, the potential benefits of such alliances may be tempered by the substantial costs incurred by inter-organizational cooperation. Therefore, this study examines the effects of the government’s strategic alliance policy on the efficiency of the participating hospitals.

Methodology

Data

To reduce the differences in technology and the quality of care among the hospitals studied, we only considered general hospitals controlled by the DOH.

Inefficient administrative systems and rising costs have forced public hospitals to find ways to improve their performance. One popular way to reduce costs and improve efficiency is for hospitals to form strategic alliances. To analyze the effects of such alliances on the performance of public hospitals, we should consider both financial and non-financial information (Carey & Dor, 2004, 2008; Yigit, Tengilimoglu, Kisa, & Younis, 2007). For this study, we obtained financial information from the participating hospitals’ websites and non-financial data from the DOH for the period 2001–2006. Since the SHAs were formed in 2004, we designated 2001–2003 as the pre-SHA period and 2004–2006 as the SHA period. Our primary objective was to evaluate the impact of SHAs on hospitals by measuring the changes in their efficiency between the pre-SHA period and the SHA period. Note that we did not consider general hospitals that had adopted total management contracts to improve their efficiency. The final data set covered 17 hospitals and included 102 observations.

Research model

The DEA has been widely used to measure efficiency in the healthcare industry (Chu, Liu, & Romeis, 2002; Hsieh, Clement, & Bazzoli, 2010; O’Neill, Rauner, Heidenberger, & Kraus, 2008; Özgen & Ozcan, 2002; Özgen & Sahin, 2010; Sikka, Luke, & Ozcan, 2009). Following prior studies (Chang, 1998; Chu et al., 2004; Hsieh et al., 2010;
O’Neill et al., 2008), we estimated the basic DEA model by pooling data from six consecutive sample years. Hence, a longitudinal data set of public hospitals for the period 2001–2006 was compiled to perform our analyses (i.e. 17 hospitals for each year and a sample of 102 hospital-years). The approach assumes that the hospitals used the same technologies to provide services during the entire 6-year period. This assumption is reasonable because the time period covered by the sample was relatively short. Specifically, the model measures the technical efficiency of a hospital relative to the performance of other hospitals. The technique is attractive because of its ability to incorporate multiple inputs and outputs simultaneously. Moreover, it provides an ideal benchmark for assessing the performance of an alliance because it generates an optimal solution (Sikka et al., 2009).

First, we applied the basic DEA model to measure the technical efficiency of the hospitals in our sample. Then, we used the Tobit regression analysis to investigate the effects of participating in SHAs on the efficiency of the hospitals by controlling for other factors (e.g. the size of each hospital, the degree of competition, and the quality of patient care) that may also affect a hospital’s efficiency.

**The DEA**

In the DEA, two behavioral models can be used to investigate the technical efficiency of an organization. One is the input orientation model, which assesses the minimal use of various inputs, while keeping the outputs constant. The other is the output orientation model, which attempts to maximize the outputs, given a fixed level of inputs. The choice of model depends on whether the management’s priority is to reduce inputs or increase outputs in order to improve efficiency. We followed prior studies (Bates, Mukherjee, & Santerre, 2006; Langabeer & Ozcan, 2009; Lee, Chun, & Lee, 2008; O’Neal, Ozcan, & Ma, 2002) and used the input orientation model because we believed that it is more appropriate for our analysis.

In Taiwan, hospitals are subject to a number of government-imposed cost-containment measures, such as the case payment system, which is a simplified version of the diagnosis related groups method implemented in the USA. Under the system, hospitals are reimbursed at a fixed rate based on the number of essential diagnoses and procedures. Because revenues are fixed, a hospital’s profit depends on the management’s ability to control costs rather than increase the volume of services provided. Therefore, we modeled hospitals as multi-input and multi-output decision making units, which attempt to minimize inputs based on a pre-determined level of outputs and technology.

In the DEA, the assessment of efficiency varies according to the assumptions made about returns to scale. Two models are widely used to identify the efficiency frontier: the constant-returns-to-scale (CRS) model and the variable-returns-to-scale (VRS) model (Cooper, Seiford, & Tone, 2000). Following prior studies (Banker, 1996; Chakraborty, Biswas, & Lewis, 2001; Chu & Liu, 2008; Chu et al., 2004), we determined which assumption best matches our data by using the DEA-based statistical tests before conducting further empirical tests.

**Identifying relevant inputs and outputs**

Based on a review of the literature (Barbetta, Turati, & Zago, 2007; Chu et al., 2002; Dacosta-Claro & Lapierre, 2003; Lambiase & Harrison, 2007; Linna, 2000; Lyroudi, Glaveli, Koulakiotis, & Angelidis, 2006; Marlin, Huonker, & Sun, 2002; Özgen & Ozcan, 2002) and isotonicity tests, we define two types of inputs: medical costs and administration costs. Medical costs include wages and salaries paid for direct labor,
expenditure on pharmaceuticals and other medical supplies, depreciation costs, and miscellaneous operating costs. Administration costs include wages paid for indirect labor, the cost of other non-medical materials and supplies, other depreciation costs, depletion and amortization costs, and other operating costs. Outputs comprise medical revenues (including outpatient revenue, hospital revenue, and other medical revenues), the number of patient emergency room visits, the number of surgical procedures, and the number of patients requiring high-technology procedures, such as computed tomography and magnetic resonance imaging scans.

**Tobit regression**

We also followed prior studies (Ancarani et al., 2009; Brown & Pagán, 2006; Chen et al., 2005; Chu et al., 2004; Lee et al., 2009) and used Tobit regression to control for factors that may explain the observed differences in efficiency across hospitals in addition to their participation in SHAs. Since the efficiency scores computed by the basic DEA model are censored at zero, OLS regression tends to produce biased and inconsistent parameter estimates (Greene, 2008). Tobit regression, on the other hand, assumes that a number of the dependent variable’s values will be clustered at a limiting value; thus, it is suitable for our analysis.

In Tobit regression, the dependent variable is the efficiency score of the basic DEA model (EFFICIENCY), and the effect of SHAs is measured by a dummy SHA variable. In addition to SHAs, we used a number of factors as control variables because they can also influence hospital efficiency. Some studies argue that larger hospitals may have higher costs and could be less efficient (Chirikos & Sear, 2000). By contrast, other studies suggest that in Taiwan, larger hospitals are more efficient (Chang, Wang & Hsiao, 1998; Chu et al., 2002). Specifically, the number of beds (LBED) is used as a proxy for hospital size (Chu et al., 2002; McCue & Kim, 2005; Younis, 2004). The degree of competition (COM) may also affect hospital efficiency (Chu et al., 2002). Following previous studies (Burgess & Wilson, 1998; Fizel & Nunnikhoven, 1993; Graham & Cowing, 1997), we employed the Hirschman–Herfindahl index to measure the degree of competition and used it to control for a hospital’s location. The index decreases as the degree of competition increases. A number of studies have also argued that there is an important link between reduced costs and the length of patient stays (ALOS) (Barbetta et al., 2007; Chirikos & Sear, 2000). Hospital efficiency may also be influenced by occupancy rates (OCC), as shown by Chirikos and Sear (2000) and Pilyavsky et al. (2006), who found that hospitals with higher occupancy rates are likely to have occupancies approaching their committed service capacity. Like prior studies in Taiwan (Chang & Hung, 2008; Chu, Wang & Shiu, 2009), we used unadjusted mortality rates (DTR) as a control variable. The rationale for this is that lower mortality rates may indicate a less complex hospital case mix and, therefore better overall performance. Based on this assumption, we posit that hospitals with lower mortality rates are more efficient. Finally, we also considered dummy years in the Tobit regression model to control for the effects of different years.

The following model summarizes the above discussion:

\[
\text{EFFICIENCY} = \beta_0 + \beta_1 \text{SHA} + \beta_2 \text{LBED} + \beta_3 \text{COM} + \beta_4 \text{ALOS} + \beta_5 \text{OCC} + \beta_6 \text{DTR} + \epsilon,
\]

where EFFICIENCY is the efficiency score derived by the DEA model; SHA is 1 if the observation is in the SHA period; otherwise, it equals 0; LBED is the natural log of the...
number of hospital beds;\textsuperscript{7} COM is the degree of competition, as measured by the Hirschman–Herfindahl index. Here, the index is defined as \( \sum_{i \in K} \left( \frac{\text{BED}_i}{\sum_{i \in K} \text{BED}_i} \times 100 \right)^2 \), where \( \text{BED}_i \) is the number of beds of the \( i \)-th hospital in health area \( K \).\textsuperscript{8} The degree of competition increases as the Hirschman–Herfindahl index decreases. The maximum index is 10,000, which indicates that there is only one hospital in the health area \( K \); hence, it does not have any competition; ALOS is the average length of stay (the total number of inpatient days divided by the total number of patients admitted); OCC is the percentage of staffed beds occupied during a reporting period. Specifically, OCC is defined as: (the total number of inpatient days/number of the staffed beds \( \times \) days in the reporting period); and DTR is the net mortality rate.\textsuperscript{9}

\textbf{Results}

\textit{Descriptive statistics}

Table 1 details the descriptive statistics of the input and output variables. The results show that the differences between inputs and outputs across hospitals in the study were substantial. Therefore, the DEA is suitable for measuring hospital performance because it can incorporate multiple inputs and outputs simultaneously.

\textbf{Test of returns to scale}

As mentioned earlier, in the DEA, the assessment of efficiency varies according to the assumptions made about returns to scale (i.e. the CRS and VRS models). Table 2 shows that the null hypothesis of a constant return to scale is rejected at the significance level under an exponential or a half-normal distribution. Statistical tests suggest that the

\begin{table}[h]
\centering
\begin{tabular}{lrrrr}
\hline
\textbf{Variables} & \textbf{Mean} & \textbf{Standard deviation} & \textbf{Minimum} & \textbf{Maximum} \\
\hline
\textbf{Input items} & & & & \\
Medical costs & 33,125,886 & 20,140,619 & 5,134,317 & 76,736,068 \\
Administration costs & 1,648,813 & 843,125 & 562,001 & 4,844,383 \\
\hline
\textbf{Output items} & & & & \\
Medical revenues & 29,661,938 & 19,456,176 & 3,028,723 & 70,704,572 \\
The number of emergency visits & 27,391 & 20,902 & 862 & 83,863 \\
The number of surgical procedures & 4,071 & 3,142 & 192 & 11,864 \\
The number of visits requiring high-technology procedures & 4,763 & 6,740 & 93 & 45,584 \\
\hline
\end{tabular}
\caption{Descriptive statistics of inputs and outputs of DEA (\( N = 102 \)).}\textsuperscript{a}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{lccc}
\hline
\textbf{Distribution of the efficiency value} & \textbf{H0} & \textbf{H1} & \textbf{F-statistics} \\
\hline
Half-normal distribution & Constant return to scale & Variable return to scale & 1.56\textsuperscript{***} \\
Exponential distribution & Constant return to scale & Variable return to scale & 2.27\textsuperscript{***} \\
\hline
\end{tabular}
\caption{Tests of returns to scale.}
\end{table}

\textsuperscript{a}Medical costs, administration costs, and medical revenues have been converted to US dollars. One US dollar is equivalent to approximately 28 New Taiwan Dollars.

\textsuperscript{7}COM is the degree of competition, as measured by the Hirschman–Herfindahl index. Here, the index is defined as \( \sum_{i \in K} \left( \frac{\text{BED}_i}{\sum_{i \in K} \text{BED}_i} \times 100 \right)^2 \), where \( \text{BED}_i \) is the number of beds of the \( i \)-th hospital in health area \( K \).

\textsuperscript{8}The degree of competition increases as the Hirschman–Herfindahl index decreases. The maximum index is 10,000, which indicates that there is only one hospital in the health area \( K \); hence, it does not have any competition.

\textsuperscript{9}ALOS is the average length of stay (the total number of inpatient days divided by the total number of patients admitted); OCC is the percentage of staffed beds occupied during a reporting period. Specifically, OCC is defined as: (the total number of inpatient days/number of the staffed beds \( \times \) days in the reporting period); and DTR is the net mortality rate.
efficiency scores in this study should be computed under the assumption of variable returns to scale.

The effects of SHA membership on hospital efficiency

The descriptive statistics of the independent variables used in the regression model are detailed in Table 3. In most of the variables, the degree of variance is large, indicating that it may also influence hospital efficiency. Therefore, we control for the variables in the following analysis.

Table 4 shows the means of the efficiency score, hospital size, length of patient stays, occupancy rates, and mortality rates before and during the SHA periods. The mean of the efficiency scores increases during the SHA period, suggesting that SHA membership improves hospital efficiency. However, the result must be interpreted carefully because other related control variables that influence hospital efficiency cannot be controlled in the descriptive statistics. Therefore, we used the regression approach to assess the impact of SHAs on hospital efficiency.

The results given in Table 5 show that the SHA coefficient is positive and significant ($t = 1.99, p < 0.05$) after controlling for the effects of different years. In other words, hospital efficiency improved following the formation of SHAs. Meanwhile, the results of the control variables show that smaller hospitals located in competitive areas$^{10}$ are more efficient, as exemplified by shorter patient stays, higher occupancy rates, and lower mortality rates.

Sensitivity analysis

The descriptive statistics given in Table 1 show that administrative costs are much lower than medical costs. To test the robustness of our results, we also used the effects of participation in SHAs on the efficiency of public hospitals without considering administrative costs. The unreported results are consistent with those listed in Table 5 (detailed statistics

Table 3. Descriptive statistics of independent variables ($N = 102$).

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>LBED</td>
<td>6.07</td>
<td>0.48</td>
<td>4.73</td>
<td>7.01</td>
</tr>
<tr>
<td>COM</td>
<td>1,230.82</td>
<td>776.94</td>
<td>308.75</td>
<td>3,177.63</td>
</tr>
<tr>
<td>ALOS</td>
<td>12.70</td>
<td>6.83</td>
<td>5.15</td>
<td>48.63</td>
</tr>
<tr>
<td>OCC</td>
<td>0.52</td>
<td>0.14</td>
<td>0.19</td>
<td>0.85</td>
</tr>
<tr>
<td>DTR</td>
<td>1.13</td>
<td>0.74</td>
<td>0.00</td>
<td>3.57</td>
</tr>
</tbody>
</table>

Note: Definitions of the variables: LBED, COM, ALOS, OCC, and DTR represent the size of the hospital, the degree of competition, the length of patient stays, the occupancy rate, and the net mortality rate, respectively.

Table 4. Means of related variables ($N = 102$).

<table>
<thead>
<tr>
<th>Variables</th>
<th>Before SHA period</th>
<th>SHA period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency score</td>
<td>0.92</td>
<td>0.94</td>
</tr>
<tr>
<td>Number of beds</td>
<td>448</td>
<td>515</td>
</tr>
<tr>
<td>Length of stay</td>
<td>11.90</td>
<td>13.50</td>
</tr>
<tr>
<td>Occupancy rate</td>
<td>0.50</td>
<td>0.54</td>
</tr>
<tr>
<td>Net mortality rate</td>
<td>1.12</td>
<td>1.13</td>
</tr>
</tbody>
</table>
are available on request). That is, the results support the argument that hospital efficiency increased following the formation of SHAs (t = 2.68, p < 0.01).

### Discussion and conclusions

In this study, we have examined the effects of forming strategic alliances on the efficiency of hospitals controlled by the DOH in Taiwan. We collected data on general hospitals in that category for the period 2001–2006. First, we applied the basic DEA model to measure hospital efficiency. Then, we used the Tobit regression analysis to investigate the effects of participation in SHAs on hospital efficiency by controlling for other factors (e.g. the size of each hospital, the degree of competition, and the quality of patient care) that may also affect hospital efficiency.

Our empirical findings suggest that, in Taiwan, the performance of hospitals controlled by the DOH improved after they formed SHAs. Moreover, the results support the conclusions of previous studies (Baker, 2001; Clement et al., 1997; Dranove et al., 2002; Halverson et al., 1997; Plochg et al., 2006; Williamson, 1981; Zuckerman, 2006), and further demonstrate the important role played by SHAs in the healthcare field. From Taiwan’s experience, we infer that SHAs improve the performance of public hospitals. We therefore hope that the results of this study will encourage health policy officials and healthcare organizations in other countries to implement similar strategies for their public hospitals.

Our study has some limitations that we should acknowledge. First, because the financial data of non-DOH public hospitals in Taiwan is not available, we cannot use the before-and-after design with a comparison group comprising hospitals that are not members of SHAs. As a result, possible bias or threats to internal validity may exist in our analyses.

Second, like many prior studies, we cannot fully capture the quality of health outcomes. Although higher mortality rates do not always indicate lower quality, lower mortality rates may actually indicate a less complex hospital case mix. Mutter, Rosko, and

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**Table 5. The effects of participation in SHAs on the efficiency of public hospitals (N = 102).**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Predict sign</th>
<th>Coefficient</th>
<th>t-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>N/A</td>
<td>0.99</td>
<td>15.91***</td>
</tr>
<tr>
<td>SHA</td>
<td>?</td>
<td>0.03</td>
<td>1.99**</td>
</tr>
<tr>
<td>LBED</td>
<td>−</td>
<td>−0.02</td>
<td>−2.16**</td>
</tr>
<tr>
<td>COM</td>
<td>?</td>
<td>−1.72E−05</td>
<td>−3.14***</td>
</tr>
<tr>
<td>ALOS</td>
<td>−</td>
<td>−3.09E−03</td>
<td>−4.89***</td>
</tr>
<tr>
<td>OCC</td>
<td>+</td>
<td>0.27</td>
<td>8.62***</td>
</tr>
<tr>
<td>DTR</td>
<td>−</td>
<td>−0.02</td>
<td>−3.81***</td>
</tr>
<tr>
<td>Dummy year</td>
<td>Included</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chi-square</td>
<td></td>
<td>87.49 (p &lt; 0.001)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Definitions of the variables: SHA equals 1 if the observation was made during the SHA period and 0 otherwise. LBED, COM, ALOS, OCC, and DTR represent the size of the hospital, the degree of competition, the length of patient stays, the occupancy rate, and the net mortality rate, respectively.

*The chi-square test is based on a likelihood ratio test, which assesses the joint significance of the independent variables (Chilingerian, 1995). This statistic is calculated by \(-2\log LR\), where \(\log LR\) is the difference between the maximized value of the likelihood function for the full model and the maximized value if all coefficients, except the intercept, are zero. The result indicates the significance of the Tobit model and is similar to an \(F\)-score test in standard regression.

**Statistical significance at the 5% level.

***Statistical significance at the 1% level.
Wong (2008) found that controls for quality and patient burden of illness can have a non-trivial impact on hospital inefficiency. As a result, inefficient hospitals could be treating patients who are more seriously ill or providing better outcomes. In this study, we used unadjusted mortality rates because of the lack of data. However, unadjusted mortality rates can produce biased results because hospitals may differ in terms of the features that affect their mortality figures. Future studies should consider the effects of the quality of care in greater depth by using measures proposed in the literature (i.e. indicators such as the adjusted mortality rate) if such data become available in Taiwan.

Notes

1. Financial information was obtained from the participating hospitals’ websites. Publication of the information began in 2001; hence, our sample period started in 2001.
2. In 2004, the alliances comprised 22 general hospitals, including 4 hospitals that had adopted total management contracts and 1 hospital that had restructured during that year. Because those hospitals’ performance indicators could have affected our results, we excluded them from our sample.
3. Isotonicity tests ensure that the relationship between outputs and inputs is positive.
4. Although administration costs are much lower than medical costs, prior studies (Dacosta-Claro & Lapi erre, 2003; Lambiase & Harrison, 2007; O’Neill et al., 2008; Valdmanis, Kumanarayake, & Lertiendumrong, 2004; Sikka et al., 2009) showed that administration costs are one of the important inputs used to measure reductions in expenditure. Thus, in addition to medical costs, we followed prior studies (Chirikos & Sear, 2000; Linna, 2000; Navarro-Espigares & Torres, 2011; Valdmanis, 1992) and considered administration costs as another important input.
5. We also included health areas as dummies in the Tobit regression model to control for the location effect. The results are consistent with the view that SHAs enhance the performance of hospitals controlled by the Department of Health.
6. Because the mean efficiency score of the hospitals increases over time (detailed statistics are available on request), we need to control for the year effect.
7. Following McCue and Kim (2005), we use the natural log of the numbers of beds to minimize variances among the hospitals in our analysis.
8. In Taiwan, the Research, Development and Evaluation Commission of the Department of Health defines 18 health areas, and the government allocates medical resources to hospitals based on where they are located. The areas are Taipei, Kaohsiung, Keelung, Hsinchu, Taichung, Tainan, Chiayi, Taoyuan, Ilan, Miaoli, Changhua, Nantou, Yunlin, Pingtung, Penghu, Hualien, Taitung, and Kinmen & Matsu. We follow prior studies (Chu et al., 2002, 2004) and calculate the Herschman Herfindahl index based on the distribution of the total number of hospital beds in the health area (i.e. $K = K_1, K_2, \ldots, K_{18}$) in which a hospital is located.
9. We use the following strict definition of the mortality rate: the number of deaths among patients who were admitted in a specific 48-h period.
10. The Hirschman Herfindahl index decreases as the degree of competition increases. The sign of ‘COM’ is significantly negative in Table 5, indicating that hospital efficiency increases as the index decreases (the degree of competition increases). Thus, we conclude that hospitals located in competitive areas are more efficient.

References


