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Efficiency of Thai provincial public hospitals after the introduction of National Health Insurance Program

By

R. Amy Puenpatom and Robert Rosenman

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1. Introduction

Many international institutions, including the World Bank and the World Health Organization (WHO), have recommended that countries adopt universal health care coverage, believing that adequate health care is a basic human right. Thailand became the first developing country to introduce universal coverage (UC) in 2001. Six of 92 provinces adopted UC in April 2001, while the remaining provinces implemented UC in October of that year. During the early phase, Thailand has struggled with implementing universal health coverage. One of the primary problems is the financial stress of public hospitals due to the mostly unfunded government mandate requiring these hospitals to meet the service needs of the enrolled population.

UC has brought at least two significant changes in Thai health care system. First, public hospitals face increased demand from the 75% of the population previously not covered by any formal insurance system. The government believes this immense demand for health care can be met by increased efficiency rather than increased capacity. Second, the hospital funding system has moved from almost no capitated payments to nearly full capitation. Before 2001, the only public health insurance program using capitation was the Social Security Scheme (SSS), which covered only 9% of the population in 2000. With UC fully implemented almost 90% of the population is now covered by capitation. Since UC capitation is geographically mandated, hospitals have fixed revenues; thus, any hospital's financial viability depends on its ability to control costs.

One goal of using capitation is to provide a financial incentive for increased efficiency among public hospitals. The purpose of this study is to investigate the short-term effect of the capitated system on hospital efficiency by comparing the technical efficiencies of public hospitals before and after the transition period during which universal coverage was implemented. In addition, the paper evaluates other hospital and service area characteristics, which might help explain technical efficiency. Among the factors investigated are geographic regions, religion, and competitions from private sector hospitals.

Our analysis focuses on regional and general public hospitals outside of Bangkok. Regional and general hospitals are the main referral hubs (for more complicated discharges) from community hospitals, most of which are located in rural areas. This requires expensive high-technology-related medical services, which the capitation payments to hospitals under UC may not sufficiently cover. Early analysis indicates that large regional and general hospitals have been more significantly affected by financial pressure from the budget allocation of the national health insurance program than community hospitals (Na Ranong et al., 2002). These public hospitals, unlike private hospital, are obligated to enroll in the UC program. While private hospitals may be voluntary enroll in UC, few have chosen to do so[1]. We exclude Bangkok from the sample because its health care market is too different from the rest of the country to treat it similarly, mostly because competition from private hospitals in Bangkok is significantly higher than those in other provinces. In fact, about 40% of all private hospitals in Thailand are in Bangkok.

[1] Private hospitals that have voluntary enrolled in the program accounts for less than one percent of all hospitals currently enrolled in the plan. Most that have enrolled are in Bangkok.

Our technical approach is to measure efficiency using bootstrap Data Envelopment Analysis (DEA), a nonparametric approach based on linear programming, and then use statistical methods to find those hospital and community characteristics that affect hospital efficiency. This is a methodological contribution to efficiency analysis of health care institutions. Banker (1993) provides a statistical foundation for the estimates of efficiency based on the Data Envelopment Analysis (DEA) that shows that they are biased for finite samples; thus inferences based on such estimates are unreliable. However, DEA estimates do exhibit the asymptotic property of consistency, so bootstrap methods provide one way to overcome the bias. Although a large number of studies have focused on the efficiency for various health care institutions, to our knowledge, none has as yet applied the bootstrap method. This paper provides an early study of hospital efficiency incorporating the DEA bootstrap model (Bodin and Simar, 2003) into a two-stage analysis to identify sources of inefficiency.

The remainder of this paper is organized as follows. Section 2 introduces and briefly reviews the Thai health care system and its national insurance reform. The general literature on hospital efficiency measurement is reviewed in section 3. Section 4 discusses the empirical methodology and efficiency estimation. Section 5 describes the sample selection and variable measurements while section 6 discusses the analytical approach for identifying sources of inefficiency. Section 7 provides the empirical results, and a final section presents conclusions and implications.

2. Background: Health Care and Health Insurance in Thailand

In 2000 there were 1,293 hospitals in Thailand comprised of 939 public hospitals, 9 state-enterprise hospitals, 14 municipal hospitals and 331 private hospitals. Of the 939 public hospitals and community hospitals, 92 are regional/general hospitals consisting of 25 regional hospitals, 48 large general hospitals and 19 small general hospitals[2]. Public hospitals are under the Ministry of Public Health (MOPH) and are operated as not-for-profit organizations, accounting for almost 75% of the nation's hospital beds (see Table 1). Community hospitals services are limited to only primary care, range from less than 10 to 150 beds. They are mostly located in districts or minor-districts in rural areas. General hospitals consist of 200 to 500 beds, while regional hospitals are equipped with over 500 beds. Both regional and general hospitals provide tertiary care and primary care services. Public hospitals have been mandated by MOPH to provide medical services for the poor and those who enroll in welfare programs. Physicians in Thai public hospitals are employees of the hospital and as such are paid by the MOPH, according to budgetary structures, through the hospitals.

UC was gradually introduced starting in April 2001. It was implemented nationwide (except some areas of Bangkok) in October, and by April of 2002; all 76 Thai provinces were included. Before the introduction of the UC health insurance programs were classified into four main categories according to their target group (Table 2). The Civil Servant Medical Benefit Scheme (CSMBS) is a health insurance program offered as a fringe benefit to government employees, state enterprises employees, and their dependents. It covers less than 10% of the Thai population. CSMBS, which continues under UC, provides more extensive coverage than other insurance programs. It is fee-for-service plan, which reimburses public

[2] State enterprise hospitals are hospitals under state jurisdiction. Four of the nine such hospitals are located in Bangkok. Most municipal hospitals (11 out of 14), which are under provincial control, are located in Bangkok. Designation as a regional, large general, or small general hospital is based primarily on size.

hospitals based on actual patient care, and pays a considerable share of the costs if the insured chooses to use private rather than public health care services. A second form of insurance that existed prior to UC and also still continues after its implementation is the Social Security Insurance Scheme (SSS). SSS provides insurance for private sector employees and the self-employed. It is a capitated system, covering about 13% of the population, half through private sector providers[3].

Prior to UC there were two public insurance programs which offered limited health care coverage to those not covered under SSS or CMSB. The Public Welfare Scheme (PWS) provided free medical care for the poor, the elderly, children, and war veterans. The voluntary health card (VHC) covered people who were not eligible for PWS. In 2000, this amounted to about 17.5% of the population. VHC offered only limited coverage, and was seen as a temporary measure in the pre-UC period (Tangcharoensathien et al., 2002). Approximately one percent of the population purchased their own private insurance. During the last decade, the number of Thais with no insurance dropped significantly from almost 70% in 1991 to 20% in 2000. However, that still left about 12 million Thai people without any health insurance coverage until the advent of UC. To sum up, access to care depended upon the ability to pay, and most citizens were not afforded equal access, despite some inadequate welfare programs.

The reform combined the PWS and VHC with the uninsured into the UC program and improved. It now accounts for more than 75% of the population. Thus, after 2001, the three public health insurance programs; CSMBS, SSS and UC, provide health coverage to almost

[3] There were 137 public providers and 132 private providers in SSS in 2003.

the entire population (Table 2). Donaldson et al. (1999) and Suraratdecha et al (2005) provide a good review of the Thai health insurance programs and benefits.

Under the new reform, UC employs a fixed capitation payment that is financed by general taxes and a co-pay of 30 baht ($0.75) per hospital visit regardless of actual expenses[4]. The capitation payment covers a wide-range of benefits packages, including most ambulatory and hospital care, and preventive care and promotion except cosmetic care, obstetric delivery beyond two pregnancies, organ transplantation, infertility treatment, and other high cost interventions. Two differences between the UC and the PWS are that PWS benefit coverage is limited comparing to UC and PWS reimbursed designated public health providers based on a fee-for-service basis, not by capitation.

3. Literature Review

3.1. Capitation and Efficiency

Efficiency in general is defined as the absence of waste. An efficient unit utilizes all of its available inputs and produces the maximum amount of output, given present technological knowledge. Equivalently, the Pareto-Koopmans notion of efficiency states that a decrease in any input must require an increase in at least one other input or a reduction in at least one output (Koopmans, 1951).

Although policy makers have often used capitation in an attempt to improve efficiency in medical care delivery, the literature on the effect of capitation is inconclusive. Chu et al. (2004), using the data from California hospitals, found that less efficient hospitals

4 A capitation payment is made to every hospital depending on the UC population. In 2002, the capitation payment was 1,204.30 baht (approximately $30 per person). The capitation rate has been increased slightly thereafter.

are more likely to be in capitated contracts. Conrad et al. (1996) studied that impact of individual dimension of hospitals' managed care strategies on hospital efficiency using the cost per discharges as a dependent variable. They found that the proportion of hospital revenues that came from capitation payments was negatively correlated with costs per hospital discharge. Heflinger and Northrup (2000), exploring a children's mental health services project, found decreases in access to services and the length of stay because of the capitated contract, but they concluded that the overall effect of capitation funding was unclear.

Worthington (1999) argued that public hospitals may be relatively inefficient because of governmental budgetary constraints; thus the ability of public hospitals to provide an acceptable service depends mainly on the level of funding and the extent of pressures on health care spending, which would argue for increased efficiency if capitation is low. In that regard, Barnum and Kutzin (1993) suggested that the capitation payment could ensure quality of care and cost containment for compulsory insurance program. Although not a study of the effect of capitation on hospital efficiency, Mills et al. (2000), looked at how other Thai providers responded to capitation payment, and found that some evidence of lower treatment quality. Leger (2000), applying a game theory model, indicated that capitation encourages the under-provision of medical care.

3.2. Efficiency Measurement in Healthcare

Two different techniques have primarily been used to measure efficiency of healthcare institutions; stochastic frontier analysis (SFA) and data envelopment analysis (DEA). SFA is a parametric regression based approach, while DEA is nonparametric – thus avoiding the need to specify a functional form and make distributional assumptions regarding residuals in the regression analysis. DEA readily incorporates multiple outputs, so it is particularly useful for measuring efficiency for hospitals which usually have multiple outputs and multiple inputs, and can calculate both technical and scale efficiency using only information on output and input quantities (Abbott and Doucouliagos, 2003). Moreover, DEA is likely to be more appropriate than stochastic frontiers in the non-profit service sectors where prices are difficult to define (Coelli, Prasada Rao, and Battese, 1998).

Thus, DEA has frequently been used to measure efficiency in studies of health care organizations. Valdmanis et al. (2004), Abbott and Doucouliagos (2003), Chang (1998), Rosenman et al. (1997) among others, have used DEA in recent studies of hospital efficiency in industrial countries and developing countries. In a particularly relevant application, Valdmanis et al. (2004) used DEA to investigate the performance of 68 Thai public hospitals in 1999 on the care of poor and nonpoor patients. She found that all types of patients are treated equally. Chilingerian and Sherman (2004) provide a comprehensive review of health care applications using DEA.

Most studies of efficiency in health care organizations using DEA have applied a two-stage approach. Efficiency is estimated in the first stage using DEA. Then, in the second stage, the efficiency estimates obtained from the first stage are used as a dependent variable in a regression equation (usually a censored Tobit) to identify environmental variables which affect efficiency (Chilingerian (1995), Grootendorst (1997), Kirjavainen et al. (1998), Hamilton (1999), Worthington (2001), Wang et al. (2003), Scheraga (2004) among others). However, as noted earlier, Banker (1993) showed that statistically analyzing DEA estimates is appropriate only asymptotically (see also Desli and Ray, 2004). In addition, Simar and Wilson (2003) indicated that DEA efficiency estimates are serially correlated, thus using conventional DEA in the two-stage approach is invalid. Therefore, statistical inference and hypothesis tests cannot be conducted directly with the estimated efficiency scores. However, bootstrap methods may be used to resolve these problems. Although several studies including Xue and Harker (1999) and Ferrier and Hirschberg (1997), apply a naive bootstrap method based on resampling from an empirical distribution, in attempt to correct the statistical problems with DEA, the naive bootstrap method is inconsistent in the context of nonparametric efficiency estimation (Simar and Wilson ,1999a, 1999b, and 2000).

Simar and Wilson (2003), building upon earlier DEA estimation by bootstrapping by Ferrier and Hirschberg (1997), and Simar and Wilson (1998, 2000), among others, suggest a bootstrap DEA method for inference and hypothesis testing in the case of DEA estimators with multiple inputs or outputs. Recently, Bodin and Simar (2003) propose a simple way of bootstrap DEA to construct confidence intervals for the efficiency scores. The Monte Carlo experiments, estimating the coverage probabilities of the estimated confidence intervals, confirm that the coverage probabilities are as good as those reported in the Monte-Carlo experiments for the full bootstrap approach (see Simar and Wilson, 2004).

4. Efficiency measurement

4.1 The basic concept of efficiency[5]

The concept of Technical efficiency can be shown conceptually using a simple example of a two-input production process in Figure 1. The isoquant shows the technically efficient hospital service levels associated with each combination of inputs. Technical

[5] This description and the following technical section is based on Rosenman and Friesner (2004), which borrowed from Coelli, Prasada, and Battese (1998).

efficiency compares how actual output compares to the ideal or the best production of this isoquant. Thus, technically efficient production assumes that reducing the use of one type of input without adding more of another type would result in reduced output. If a hospital uses the combination of inputs (K and L) indicated by point Y to produce the level of services associated with the shown isoquant, it is using more inputs than is technically needed. Technical efficiency (TE) is measured by the ratio 0X/0Y. When TE is equal to one, a firm's actual production point lies on the frontier, which is efficient. If it lies below the frontier then it is technically inefficient.

A related issue is scale efficiency. The output frontier from a single input production function provides the easiest insight into the calculation of scale efficiencies. Figure 2 shows a production function where some single input produces an output generically called hospital services. Two production frontiers are shown, one assuming constant returns to scale (labeled "CRS Frontier") and one assuming variable returns to scale (labeled "VRS Frontier"). Scale efficiencies are found by comparing efficiency on the variable returns to scale frontier to efficiency on a constant returns to scale frontier. For example, if a hospital is producing at point B (output B_O with P_b physician FTEs) it is technically inefficient assuming either constant returns to scale or VRS. If there are constant returns to scale, technical efficiency is given by the ratio $TE_{CRS} = B_O B_C / B_O B$. Technical efficiency assuming variable returns to scale is measured as $TE_{VRS} = B_O B_V / B_O B$. Scale efficiency calculated as the ratio of these two measures: SE = $B_O B_C / B_O B_V = TE_{CRS} / TE_{VRS}$. Essentially, scale efficiency gives a rough comparison of the average product of the firm at B compared to the average product at the technically optimal point (D). Comparison to point D tells us if the firm has scale inefficiency due to being too small (in the increasing returns to scale portion of the production function, like point B), or too large (in the decreasing returns to scale portion of the production function, like point C).

4.2 Data Envelopment Analysis (DEA)

DEA is a non-parametric technique based on linear programming. It establishes an efficiency frontier by solving a series of mathematical programming problems to find the most efficient production units and measure the relative efficiency of each decision making unit (DMU). DEA originated with Farrell (1957) and was further developed by Fare and Lovell (1978), Charnes, Cooper and Rhodes (1978), Banker, Charnes and Cooper (1984) and Coelli (1996), among others. The production frontier of decision making units (DMUs) that are producing a given number of outputs with the fewest number of inputs is identified. Measured against this frontier, efficiency is measured from 0 to 1 (the most efficient). Input oriented technical efficiency measures how much a firm produces relative to the isoquant frontier that is possible with the inputs it has chosen to use. Output oriented efficiency measures how well the firm does in minimizing the amount of inputs it uses, again relative to the isoquant frontier, given the output is has chosen.

Data Envelopment Analysis (DEA) proceeds as follows. Let y_i be a vector of m outputs and x_i a vector of *k* inputs for the i^{th} firm. If we have data for *n* firms, then *X* is a $k \times n$ matrix of input data for all firms and *Y* is a $m \times n$ matrix of output data. The *envelope*, or efficiency frontier, is derived by solving the following constant returns to scale problem:

$$\min_{\theta,\lambda} \ \theta_i \text{ subject to } \quad -y_i + Y\lambda \geq 0$$

$$\theta_i x_i - X\lambda \geq 0$$

$$\lambda \geq 0. \qquad (2)$$

where λ is a $n \times 1$ vector of constants and θ_i is a scalar. The value $\theta_i \leq 1$ is the technical efficiency (TE) score for the i^{th} firm with a value of 1 meaning the firm is on the frontier, thereby efficient. The problem is solved once for each firm in the sample, giving technical efficiency scores for each.

The variable returns to scale (VRS) efficiency frontier is derived by solving the following problem:

$$\begin{aligned} \min_{\theta,\lambda} \ \theta_i \ \text{ subject to } \ & -y_i + Y\lambda \geq 0 \\ & \theta_i x_i - X\lambda \geq 0 \\ & I_v \lambda = 1 \\ & \lambda \geq 0 \end{aligned} \qquad (1)$$

where I_v is a $n \times 1$ vector of ones. The convexity constraint, $I_v\lambda = 1$, ensures that an inefficient firm is compared against firms of a similar size.

To find scale efficiency, one must first solve the constant returns to scale technical efficiency model (equation (1)). Any difference between the technical efficiency score calculated from the constant returns to scale model, θ_C, and the technical efficiency score from the variable returns to scale model, θ_V, shows scale inefficiency. Scale efficiency is measured by θ_C/θ_V.

Finally, returns to scale is found by running one final technical efficiency model which imposes nonincreasing returns to scale, by changing the third constraint in the variable returns to scale model to $I_v\lambda \leq 1$. If the technical efficiency score found from this problem is equal to the technical efficiency score found in the variable returns to scale model the firm is in its increasing returns to scale area of production. If the two scores are equal, but not equal to the technical efficiency score from the constant returns to scale model, then decreasing returns to scale apply. Obviously, if the technical efficiency score from the variable returns to scale model equals the score from the constant returns to scale model, constant returns to scale are in effect.

In this study we use an input oriented model because Thai public hospitals must meet the market demand given a level of inputs, especially hospital beds and medical staff, which is approved by MOPH. Lovell (1993) argues that such an input-orientated is appropriate in this situation. In addition, because it is more general, we use a VRS model, allowing variable returns to scale. The hospitals in our sample vary quite a bit in the number of authorized beds and the size of medical and other staff, as well as in output quantities. With such a variation in size, it would be inappropriate to assume constant returns to scale over the range of our data. Coelli, Prasada Rao, and Battese (1998) indicate that the VRS specification has been the most used specification in the 1990s.

4.3 The DEA bootstrap estimator

Bootstrapping, developed by Efron (1979), uses computer-based simulations to obtain a sample of random variables that mimic the sampling properties of a parent population. Simar (1992) introduced a DEA bootstrap approach which was developed further by Simar and Wilson (1998 and 2000). It applies a smoothed distribution of efficiency values to generate bootstrap samples of efficiencies. Smoothing is performed by an application of a kernel estimate based on the reflection method (Silverman, 1986). Bodin and Simar (2003), using the statistical model in Simar and Wilson (2000), proposed a simple bootstrap DEA to construct confidence intervals for the efficiency scores.

We apply the technique developed in Bodin and Simar (2003)[6]. First, using the input-output vectors, we construct efficiency estimates, $\hat{\theta}_i$ for each DMU_i for i =1,…,n. Second, we apply a kernel smoothing of the empirical distribution of the efficiency estimates to generate smoothed efficiencies. To obtain a consistent estimator, the choice of smoothing parameter (the bandwidth parameter) has to be chosen appropriately. For that reason, the bandwidth function rule for univariate data is recommended by Silverman (1986, eq.3.31).[7] We next simulate pseudo-data by generating values of $\hat{\theta}$ from a smooth estimate of the continuous density of $\hat{\theta}$, noting that the $\hat{\theta}_{(n)}$ =1 after eliminating all the spurious efficiency scores equal to 1 from the pseudo-sample. Third, giving *n* is the number of decision-making units (DMUs), we estimate $f(\hat{\theta})$ from the remaining $\hat{\theta}$ and generate B samples of the boundary condition $\hat{\theta} < 1$ (of the size n-1), which is $\left\{\hat{\theta}_1^{*b},...,\hat{\theta}_{n-1}^{*b}.\right\}_{b=1}^{B}$ from $f(\hat{\theta})$. We apply GAUSS to construct bootstrapping DEA using these procedures.

5. Data and Variables

As discussed above, the data consists of yearly observations of 92 regional and general hospitals located throughout Thailand, but outside Bangkok.[8] We chose this sample for two primary reasons. First, these hospitals comprise all major public hospitals in each province that provide tertiary care. They are the main referral hubs from community hospitals, thus admit more complicated discharges and provide more expensive medical

[6] A completed description of the algorithm can be found in Appendix 6.

[7] The Silverman approach finds the proper bandwidth by determining the optimal tradeoff between dispersion and ranges.

[8] Again, we excluded Bangkok ibecause its hospital market is the only one in Thailand facing significant private competition..

services, which the capitation payments to hospitals under UC may not sufficiently cover because of limited budget allocation.[9] Second, public hospitals are obligated to enroll in the UC program, while private hospitals are not obligated but can voluntarily enroll, although very few choose to do so.

Data are available for the three fiscal years from October 1999 to September 2002 (two year prior to the reform and one year after the reform).[10] The primary sources of data, including financial and activities database, is the Bureau of Health Service System Development, Ministry of Public Health (MOPH). Variables collected include the number of patient visits under different health insurance plans, the number of surgeries, number of patient visits by specialties, number of hospital beds and detailed data about health care personnel. The financial database includes revenue from different sources (including UC funding), expenses, and debts.

Gross provincial product per capita (GPPCR) and number of private hospital beds were obtained from the National Economics and Social Development Board (NESDB) and MOPH, respectively. Since UC officially started on October 1, 2001, the pre-UC period is defined as the fiscal year 2000 (October 1999 to September 2000) and 2001 (October 2000 to September 2001) and the post-UC period is the 2002 fiscal year (October 2001 to September 2002).

5.1 Variables used in DEA model

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9 We exclude community hospitals from the sample because they are in different markets in that they offer less technological services than do the general and regional hospitals. Almost 700 hospitals are community hospitals with 70 beds or less which provide only primary care service. Regional and general hospitals tended to experience financial problem because community hospitals can off-load expensive and difficult cases onto them.

10 MOPH has collected financial and activity database by administrative purpose. Although the 2003 fiscal year data are available, we were not able to use it in this study since the MOPH stopped collecting number of inpatients and outpatients visits categorized by specialties.

The DEA model includes five inputs and five outputs (table 3). Inputs consist of four categories of labor and one category of capital. Labor is measured in Full-time equivalent (FTEs) and differentiated by primary care physicians, ancillary professional care providers (dentists and pharmacists), nurses and other personnel. Since health personnel in public hospitals are paid the same across region and by tenure during the studying period, the wages of labor do not differ across regions. Capital is captured by the number of beds in each hospital.[11] Revenue generation is not part of a hospital's performance criteria, so hospitals maximize output subject to this budget constraint; thus our focus on production efficiency and input oriented DEA.

Output variables include three measuring inpatients and two measuring outpatients, adjusted for hospital-wide severity[12]. Inpatient variables, include INSUR, the number of adjusted inpatient visits in acute surgery (General surgery and Orthopedic surgery); INPRI, the number of adjusted inpatient visits in primary care, (Pediatrics, Medical, and Obstetrics and Gynecology); and INOTHER, the number of adjusted inpatient visits in others (Dental, ENT, Ophthalmology, Rehabilitation medicine, and others). The two outpatient outputs are the number of surgical outpatient visits (OUTSUR) and number of non-surgical outpatient visits (OUTNONSUR).

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[11] Management in public hospitals in Thailand is highly centralized. The government, through line-item budgets, determines the budget allocation to each hospital. Any operating budget remaining at the end of the fiscal year is surrendered back to the government so that hospitals tend to use up money at the end of each fiscal year. Thus, hospital expenses are determined by the hospital's revenue allocation from MOPH.

[12] For outputs, we need to consider severity, which may influence utilization and therefore measured efficiency. One customary approach is to adjust outputs by casemix. However, MOPH does not provide direct measures of patient severity. As an alternative we estimate overall severity within a hospital by the ratio of number of large surgeries to total surgeries, which is used to adjust all outputs. The number of adjusted inpatient visits in each group is defined as $\frac{number\ of\ large\ surgeries / small\ surgeries}{maximum\ of\ the\ numerator} \times number\ of\ inpatient\ visits$. A justification for adjusting all patients with this ratio is this; hospitals that attract a larger share of more complicated (i.e. large) surgeries likely attract more severe cases of other types of patients as well.

Table 4 provides sample means and standard deviation of all DEA variables by year. Appendices 1 and 2 disaggregate the sample means by type and by region. Output variables for the most part (INSUR, INPRI, INOTHER, OUTSUR, and OUTNONSUR) are highest in 2002, and are lowest in 2001. It is interesting that while the number of outpatient visits dramatically increased from 225,952 to 370,325 or 64% from 2001 to 2002 immediately after the UC was introduced, the number of in-patient visits slightly decreased by 4% after the UC has been introduced. In 2002, the average size of the sample hospitals is 439 beds, ranging from 85 beds to 1,143 beds. The average number of physicians, nurses, and other personnel are 50, 404, and 78 persons respectively.

MOPH classifies hospitals by number of beds. The number of health personals and beds are positively correlated with size of hospitals. The average number of beds (year 2002) in regional hospitals, large general hospitals, and small general hospitals are 689, 395, and 221 beds respectively (see Appendix 1). Regional hospitals, which are the largest hospitals in Thai health care service, generated highest outputs while; small general hospitals produced the lowest amount of services. Larger hospitals are mostly located in the eastern and northeastern regions.

6. Identifying Sources of Inefficiency

6.1. A Censored Tobit regression

The second step of the analysis is to relate the inefficiency scores, acquiring from the bootstrap DEA, to a number of explanatory variables, including observed characteristics of the hospitals and environmental variables. Since efficiency scores computed from the bootstrap DEA model, are censored at zero and one, an OLS regression that assumes a normal and homoscedastic distribution of the disturbance and the dependent variable would produce biased and inconsistent parameter estimates because the expected error will not equal to zero (Maddala, 1983). Therefore, a Tobit model is more appropriate.

Greene (2003) suggested that a convenient normalization in Tobit studies is to assume a censoring point at zero. This method is consistent with the Tobit technique developed by Tobin (1958) by using a left-censored variable. DEA measures of technical efficiency are between 0 and 1. To move to a one-sided truncation the DEA scores were transformed with the formula $INEFF_j$ = (1/TE)-1. Thus, a negative sign on a coefficient indicates a positive association with efficiency. The exact model specification is defined as follows (Chang ,1998; Chu et. al., 2003; and Kirjavainen and Loikkanen, 1998):

$$y_j^* = \beta' x_j + \varepsilon_j$$

$$y_j = \begin{cases} y_j^* & \text{if } y_j^* > 0, \\ 0 & \text{otherwise.} \end{cases}$$

where $\varepsilon_i \sim N(0, \sigma^2)$, where x_i and β are vectors of explanatory variables and unknown parameters, respectively, y_j^* is a latent variable and y_i is the observed inefficiency scores. Chilingerian (1995) points out that once DEA scores (TE) have been transformed to the inefficiency score, the slope coefficients of Tobit are interpreted in the same way as an ordinary least squares regression.

6.2 Variables used in the regressions

Table 5 shows the list of all variables used in the Tobit analysis. The inefficiency score (INEFF) is employed as a dependent variable. We calculate (INEFF) based on the result from the bootstrap DEA according to the formula above. For explanatory variables, we include a variety of hospital specific characteristics and market factors. We measure the mix of labor inputs by the ratio of FTE physicians to other full-time personnel[13] (PHYRATIO), since the proper mix of inputs can affect a hospital's efficiency. Hospital service variables include two factors. First, the number of referrals (REFER) reflects the level of services and resource consumption of each hospital. Most referrals are tertiary and emergency discharges that exist when a treatment could not be managed at the lower level health center. Having higher-level technological equipment and more physicians, large regional and general hospitals are more likely to admit patients who are referred from other small hospitals. This results in an increase in output, which could improve the hospital's efficiency, especially if the fixed equipment is "lumpy". Second, the length of stay (LOS) is often used to represent the efficiency with which individual patients are treated, although there is a potential tradeoff between length of stay and quality of care (Carey, 2000).

We also include three external market factors as explanatory variables; a Herfindahl-Hirschman index of all public and private hospitals (HI), the number of private hospital beds in each province (PRIBED) (both help capture market competition) and the Gross Provincial Product per capita (GPPCR).[14] Public hospitals in different regions generally do not compete with each other because people tend to visit public hospitals based on their geographical areas. However, hospitals in each province encounter different levels of market concentration. HI is defined as the sum of the squares of the market shares of each individual hospital where the market share is calculated by the ratio of number of beds of hospital *i* to

[13] Most full-time personnel are nurses.

[14] The value of GPPCR is in a real term (1988 constant price).

the total number of beds in each province.[15] Higher HI values reflect less competitive pressure. PRIBED is a proxy of market competition from private hospitals. Chirikos and Sear (1994) showed that inefficiency scores are higher in markets with more intense inter-hospital competition. Our model hypothesizes that the greater the number of private hospital beds, the higher the competition from private hospitals. Then, given the more health care choices available, this would result in a reduction in number of visits to public hospitals, and hence decrease efficiency of the public hospitals.

Gross Provincial Product per capita (GPPCR) represents the population's wealth in each 75 province. Provincial wealth gives at least two impacts in hospital efficiency. First, wealth may affect people behavior in seeking health care. Before UC, people who live in less wealthier region may have avoided visiting doctors if they were able to find cheaper alternative treatments, while wealthier people may seek care from either public hospitals or private hospitals; however, since private sector services are principally located in the urban areas alternative sources of health care are not always available. Thus, hospital in wealthier provinces may experience higher efficiency because of higher number of visits comparing to poorer provinces. Second, because the Thais usually provide donations for good deeds to temples and hospitals, provincial wealth may affect hospital revenues. Although the major source of public hospital revenue is from the MOPH budget, part of the revenue is from donations of people residing in the province, which increases the hospitals' reserves. This additional financial reserve could help stabilize the hospital's financial status and loosen performance, but decrease in efficiency. The influences from provincial wealth to hospital

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[15] The formula is defined as $HI = \sum_{i}^{n} \Pi^2$ where Π is the market share of a firm *i*, and n is a number of firms in that province.

efficiency are mixed because it affects both number of hospital visits and hospital financial ability.

We also include location dummy variables, categorizing the six regions in Thailand, to account for geographic heterogeneity. Figure 4 shows the map of Thailand, which comprise of northern region, northeastern region, central, east, west, and southern region. Moreover, because Thailand is predominantly Buddhist (95%), with its 4.4% Muslim population concentrated in the southernmost provinces - Pattani, Yala, Songkla, and Narathiwat, we include an Islam dummy variable (ISLAM) to capture religious differences. ISLAM indicates 1 if a hospital is located in the Muslim-dominated provinces, and 0 otherwise. Note that out of 13 Southern provinces, only the four southernmost are Muslim-dominated provinces.

Since UC has changed hospital financial sources, we added the other two variables to assess UC usage. UC usage variables include the ratio of the number of UC inpatients to UC enrollees (INUC) and the ratio of the number of UC outpatients to UC enrollees (OUTUC). Before UC, public hospitals in Thailand received different levels of budget allocations depending on available resources; after UC reform, hospitals obtained capitation payments based on the population in their areas, which has been used to regulate reimbursement. Hospitals in a highly populated area tend to be more financially stable. However, studies such as Pannarunothai et al. (2004) and Na Ranong et al., (2002) argue that the capitation rate in 2002 was not adequate. Ngorsuraches and Sornlertlumvanich (2006) indicates that various managerial variables such as patients to employees ratio, service mix, and market variables were determinants of hospital loss on the first year of UC implementation. They confirm that unprofitable hospitals tended to experience higher number of the UC inpatient days and also were located in the provinces with higher proportion of UC beneficiaries. Thus, hospitals that cared for more UC patients relative to UC enrollees are more likely to have financial shortfalls that should pressure hospital performance and increase efficiency.

Table 6 and Appendix 3 provide the descriptive statistics of explanatory variables in the 92 large public hospitals used, broken down by hospital type. The average length of stay per admission decreased slightly from 4.91 in 2000 to 4.84 days in 2001, but grew to 5.06 days in 2002. Gross Provincial Product per capita increased from 44,227 baht in 2000 to 46,931 baht in 2002. The ratio of physicians to other medical staff increased slightly from 8% in 2000 to 8.2% and 8.3% in the subsequent years. Furthermore, the average number of referrals from other hospitals (REFER) grew slightly from 9,246 to 9,762 visits over the time period 2000 to 2002. The number of referrals was the highest in the northeastern region (16,300), which was 4 times higher than the central and the west, which are smaller regions. Regarding people's wealth by region, the East had the highest gross provincial product per capita, while the northeastern region was the poorest. In addition, the UC usage ratio was approximately 20% for outpatients and 4.6% for inpatients in its first year. Northeastern hospitals admitted the highest number of UC patients relative to UC enrollments (26% for outpatients and 6% for inpatients), while the central region experienced the lowest UC outpatient utilization (16%).

6.3 Including a UC variable

In this section, we propose a model of the determinants of technical efficiency in Thai public hospitals over the period 2000 to 2002. We include a new variable (OUTUC) that existed after UC has implemented in 2002. Suppose that we define period 1 as a pre-UC period (2000 and 2001), and period 2 (2002) as a post-UC period. We assess the effect of the

UC variable whether it changed an intercept, a slope, and/or an error term. The model can be written as follows;

Period 1: $Y_1 = a + bX_{ij}^1 + e_1$ (3)

Period 2: $Y_2 = a_0 + b_0 X_{ij}^2 + cZ_i + e_2$ (4)

where X_{ij}^1 is a $n_1 \times m$ matrix of m explanatory variables of n_1 DMUs in period 1, X_{ij}^2 is a $n_2 \times m$ matrix of explanatory variables in period 2, Z is a $n_2 \times 1$ vector of UC variable, and e_1 and e_2 are $n_1 \times 1$ and $n_2 \times 1$ vectors of error terms of each period, respectively.

The full model, which is the unrestricted model, can be written as follows:

$$\text{Y} = (a + a^* D) + (b + b^* D) X_{ij} + cZ_i + e_1(1 - D) + e_2(D) \tag{5}$$

where $a_0 = a + a^* D$, $b_0 = b + b^* D$, D is a time dummy variable indicating 1 if after-UC period.

We conduct five hypotheses tests, which are 1). $H_0: a^* = 0$, 2). $H_0 : b_i^* = 0$, 3). H_0 : c = 0, 4). $H_0 : a^* = b_i^* = c = 0$, and 5). $H_0 : \sigma_1^2 = \sigma_2^2$. The first four hypotheses testing examine how the intercept, slope coefficients, and the new UC variable affect the structure of the model, employing a log-likelihood ratio test, which can be calculated by –2logλ where logλ is the difference between the log of likelihood function of a restricted model and an unrestricted model. Note that equation (5) is an unrestricted model. In order to test for the fifth hypothesis, we apply a Modified Levene Test to examine whether the error terms have constant variances. If we cannot reject the null hypothesis of homogeneity of variances, the variances in both equations are statistically equal.

7. Empirical results

7.1 DEA result

The DEA result indicates that UC improved efficiency across the country. Table 7 shows the mean of the DEA *efficiency* estimates by type of hospital during the 2000 - 2002 fiscal years. Overall, mean efficiencies in all types of hospitals slightly decreased from 0.83 in 2000 to 0.78 in 2001 immediately after the UC program was introduced, and rebounded to a higher level of efficiency in 2002 (0.86). The average efficiency score was 0.82, implying that hospitals use on average approximately 18% more inputs per unit of output than if they were all efficient. Regional hospitals, in particular, improved their efficiency the most in 2002. On average, small general hospitals were the most efficient hospitals, followed by large general hospitals and regional hospitals (0.90,0.82, and 0.75 respectively). In addition, the UC program affected six regions differently. As shown in Table 8, UC affected the southern region's efficiency the most (13.4%) while affected the North's the least by 5%.

Table 9 shows the distribution of changes in technical efficiency over time. Comparing 2000 to 2002, 50 out of 92 hospitals increased their efficiency, 14 were unchanged, and 28 decreased. But, during the transition year, from 2000 to 2001, 59 hospitals reported a decrease in efficiency while only 25 hospitals showed an increase in efficiency. After UC was fully implemented, 70% of all hospitals (65 hospitals) experienced an improvement in efficiency from 2001 to 2002, 10% reported no change, and about 20% of hospitals experienced a decrease in efficiency.

It is surprising that so many hospitals experienced a decline in efficiency from 2000 to 2001 because UC was not widely implemented until October 2001 (which is the start of the 2002 fiscal year). The implementation of UC was tied to the election victory of the Thai

Rak Thai party in February 2001. The exact chronology is given in the Appendix 4. It is possible that people, expecting that the out of pocket cost of care would decline with the implementation of UC, delayed the use of hospitals when possible. For the outpatient visits, Table 10 and 11 show that the number of both non-surgery and surgery services in both outpatients and inpatients care decreased before the beginning of UC, but increased significantly after the reform has started. It can be seen that changes in efficiency were mostly caused from changes in output since inputs (number of health personnel) increased slightly (Table 12). When inputs are rather fixed, this decrease (increase) in output would decrease (increase) efficiency.

We employ two nonparametric tests to study for average differences in efficiency by time period. First, a Kruskal-Wallis Analysis of Variance (K-W) test is conducted on the null hypothesis that there is no median difference in technical efficiency across the three years. As shown in Table 13, the chi-square is 14.9, which is greater than the 0.05 level of significance, allowing us to conclude that at least one pair of the technical efficiency medians is not equal. This provides statistical evidence that technical efficiencies in Thai provincial hospitals changed after the introduction of UC. We next utilize the Mann-Whitney U test to conduct pairwise comparisons since the Kruskal-Wallis one way ANOVA test is significant (Sheskin, 1997) of year 2000 to year 2001, year 2001 to year 2002, and year 2000 to year 2002. The results reported on Table 14 indicate that the population medians of technical efficiency are different at all pairs; 2000 and 2001, 2001 and 2002, and 2000 and 2002. This is a key finding, which suggests hospital efficiency improved from before the introduction of UC (2000) to after its introduction (2002).

Many of the efficient hospitals, those with a technical efficiency score of one, experienced a decrease in efficiency in 2001, but regain their efficiency in 2002. As we can see in Table 15, the total number of efficient hospitals was highest in 2002 (34 hospitals), compared to 13 hospitals and 22 hospitals in 2001 and 2000 respectively. Large regional hospitals were more likely to be efficient in 2002. However, some efficient large regional hospitals in 2000 experienced a decline in efficiency in 2001, although they all regained full efficiency in 2002. Appendix 5 shows the information in detail.

After UC, more northeastern hospitals were efficient than in other areas (over 70%, 14 out of 19). The performance of southern hospitals was the same before 2001, but improved in the post-UC period. Out of 19 hospitals, the number of efficient hospitals from the South increased from five hospitals in 2000 and 2001 to eight hospitals in 2002. All four efficient small hospitals in 2000 were the same hospitals in 2002.

7.2 Comparing DEA and bootstrap DEA result

Table 16 and 17 report the descriptive statistics for the bootstrap DEA scores for B = 1000 replications from 2000 to 2002. The average of the bootstrap efficiency estimates was 0.76, which is lower than the average of the (0.82) original efficiency scores. Also, the minimum and the standard deviation of the original DEA estimates for each of the years are higher than the bootstrap values (except the minimum in 2000). Efron (1982) indicates that the bias of the statistic is not a serious problem when the ratio of the estimated bias to the standard error is less than 0.25. Our result shows that approximately 65% of hospital ratios are greater than 0.25, indicating a bias problem of the original scores. Therefore, the bootstrap DEA estimates are likely better indicators of hospital technical efficiency. Figure 3 compare the original DEA and bias-corrected bootstrap DEA efficiency scores.

7.3 The regression results

In section 6.3, we formulated a model of the determinants of technical efficiency in Thai public hospitals over the pre-UC period (2000 and 2001) and the post-UC period (2002). To test whether the UC variable (OUTUC) changes the structure of the regression model, we performed five hypotheses tests.[16] Table 18 shows the Likelihood-ratio tests for parameters of the Tobit model. For the first hypothesis, testing a potential change in the intercept term over the two periods, we found that the log likelihood ratio (3.98) is greater than a chi-square statistic with one degree of freedom ($\chi^2_{(0.95;1)} = 3.84$). Thus, we can reject the null hypothesis at a 0.05 level of significance that a coefficient of a time dummy variable *D*, a^*, is equal to zero, implying the intercepts of two periods are not equal. The second hypothesis is that all slop coefficients are jointly equal to zero. We found that the model is significant with a LR test of the restriction that all the slope coefficients are jointly zero rejected at a 0.05 level [LR=22.56 ~ χ^2_{12}]. This allows us to conclude that at least one pair of the slope coefficients is not equal and the result provides statistical evidence that OUTUC may cause a change in efficiency after the introduction of UC. We also reject the third hypothesis of the coefficient of UC variable, c, being equal to zero, which implies that there is statistical evidence that OUTUC affected technical efficiencies in Thai provincial hospitals. In addition, we reject the fourth null hypothesis that the intercept, slope coefficients, and the UC coefficient are zero. Furthermore, the modified Levene test (Table 19), examining the homogeneity of variances hypothesis, does not reject the null hypothesis that the variances of both periods are equal, implying that the inclusion of the UC variable

[16] We dropped INUC due to a high collinearity. The reason for leaving OUTUC in the model is that the number of outpatients has significantly changed during the period of study, while the number of inpatients was rather constant (refer to section 5.1).

does not alter the error terms in both periods. To sum up, there is evidence that including the UC variable (OUTUC) changed the intercept, and no statistical evidence that it changed the error terms of the model, but the slope coefficients did change. Thus, the model we use for the Tobit regression in this paper is written as follows;

$$Y = (a + a^{*}D) + (b + b^{*}D)X_{ij} + cZ_{i} + e \qquad (6)$$

We, then, performed a Tobit regression using bootstrap DEA scores as a dependent variable. A set of explanatory variables includes the outpatient UC usage ratio (OUTUC), physicians to other staff ratio (PHYRATIO), the length of stay (LOS), the gross provincial product per capita (GPPCR), number of referrals (REFER), the Herfindahl index (HI), number of private hospital beds of each province (PRIBED), the Islam dummy variable (ISLAM), and six region dummy variables. The estimated coefficients and standard errors of the pre-UC and post UC parameters are shown in Table 19. Also included in the same table are statistics for Log-likelihood ratio tests. The level of significance ($\chi^2_{(1)}$ = 18.80) indicates that a random-effect Tobit model is more appropriate than the pooled Tobit regression.

As shown in table 19, the regression confirms that the introduction of UC increase hospital efficiency. The UC variable, outpatient UC usage ratio (OUTUC), has a negative and statistically significant effect on hospital technical inefficiency as expected, suggesting that an increase in number of UC patients per enrollees tends to increase efficiency[17]. After UC was implemented, those hospitals with larger UC utilization were more efficient. Because hospitals with a high percentage of UC usage tend to experience more financial problems, this result is consistent with the hypothesis that hospitals responded to the financial pressures associated with higher UC utilization by increasing efficiency.

[17] This variable (OUTUC) is zero before UC.

The other key finding about how UC affected hospital behavior shows up in the variable PHYRATIO (the percentage of physicians to other full-time personnel). PHYRATIO shows a significant positive effect in the pre-UC period. The result suggests that the hospitals that have a larger ratio of physicians to other medical staff are less efficient. Thailand has experienced a shortage in medical professionals such as physicians, dentists, and nurses for years especially in the northeast and the northern regions. The regression result implies that given a fixed number of physicians, an increase in the number of other medical professionals, especially nurses, improves efficiency. Because D*PHYRATIO has a significant negative effect in the post-UC period, we conduct the Log-likelihood ratio test (LR) to examine whether the sum of both period coefficients is significantly different from zero (Table 18). With the LR test, we cannot reject the hypothesis that the sum of PHYRATIO's and D*PHYRATIO's coefficients is zero at a 0.05 level [LR= 1.1 ~ $\chi^2_{(1)}$], indicating that the effect of PHYRATIO (lowering efficiency) disappeared after the implementation of UC. This result is interesting because it has been known that UC has caused more shortage in physicians in public sector since some switched to work in the private sector.

The base equation provides more general information about what improved hospital efficiency in Thailand, both before and after the introduction of UC. We found that number of referrals (REFER) is positively related and statistically significant with the level of efficiency in Thai public hospitals while the effect of D*REFER is not significant. This suggests that large hospitals, which admit more tertiary cases, are likely to be more efficient in both pre-UC and post-UC periods and this efficiency does not change with introduction of UC. The result is consistent with the hypothesis that an increase in the number of referrals enhances output and efficiency. Furthermore, the regression result indicates that the length of stay (LOS) is positive and statistically significant, which conforms to the a priori hypothesized signs. The shorter length of stay appears to improve the level of efficiency. With UC, the effect of LOS on technical efficiency does not change. We also show that the number of beds (BED) is not statistically significant showing that the size of hospitals does not determine hospital efficiency. This may appear to be at odds with our earlier finding that regional hospitals were less efficient than large and small general hospitals. However, the dependent variable in this regression we are measuring the marginal effect with number of beds, while in the earlier analysis we measured the average effect.

Although gross provincial product per capita (GPPCR) and D*GPPCR are not statistically different from zero at a 0.1 level of significant, they are statistically significant at a 0.15 and 0.12 level of significant respectively. Although the coefficient is small, the negative coefficients show that hospitals located in wealthy areas are more likely to be efficient. The result shows that the provincial wealth factor is positively correlated to efficiency in both periods, and the impact was stronger after UC was implemented[18]. Patients from more affluent areas on average have a greater ability to pay for hospital services than patients from poorer areas. In fact, one conjectures that people in lower income provinces tend to prefer self-care; using over-the-counter drugs or obtaining traditional care, because of the lower cost of these alternative treatments. We see this in the pre-UC data where hospitals in poorer areas tended to admit fewer patients, which lowers hospital efficiency when controlling for inputs. With UC, the cost of health care per use decreased to

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18 We reject the hypothesis that the sum of GPPCR's and D*GPPCR's coefficients is zero at a 0.05 level

30 baht per visit, so more people, regardless of wealth, were able to get access to care. Therefore, the effect of provincial wealth matters more after UC was introduced.

Most regional dummy variables were statistically significant, indicating general patterns of efficiency by geographical location. Compared with the (excluded) southern region, in the pre-UC period hospitals from the northeastern region were the most efficient, followed by the southern region. Hospitals in the west were the least efficient. The Northeast is the poorest region where people in the region have the highest ratio of population per physician, nurse and hospital than the rest of the country. Ngorsuraches and Sornlertlumvanich (2006) reports that 30% of unprofitable hospitals after UC was implemented were in northeastern. This increase in outputs as well as the higher pressure from financial difficulty induced efficiency. In contrast, it appears that there are more public hospitals in western region relative to other regions; of the 76 provinces, four out of 92 hospitals are located in Rachaburi, which is a small affluent province in the western region. It is possible that some hospital resources may not have been utilized efficiently due to the small amount of services. After UC was introduced, only the East dummy variable is statistically significant at a 0.05 level of significance, indicating that only in that region, on average, did hospital efficiency change (becoming less efficient) relative to the south. The Islam dummy variable (ISLAM) is not statistically significant in either period showing that hospital efficiency is unaffected by religious composition of population. .

Neither competition variable (PRIBED and HI) had a coefficient that statistically differed from zero. Although we hypothesized that an increase in private hospitals may improve public hospital efficiency because patients have more choices to choose where they visit, the empirical results do not support that idea. The insignificance may imply that private and public hospitals in Thailand serve different markets. Competition among private and public hospitals is limited because private hospitals tend to focus on upper-middle income to high-income market because they usually provide more courteous and luxurious services while public hospitals provide care at a lower cost for a lower income group.

8. Summary and Conclusions

This paper investigates the short-term effect of the new national health insurance known as Universal Coverage on hospital efficiency by comparing the technical efficiencies of public hospitals before and after the transition period during which universal coverage was implemented. We studied the efficiency differences among 92 Thai provincial public hospitals using a two-stage analysis, including the Data Envelopment Analysis, bootstrapping DEA, and a censored Tobit model.

In all, the DEA results indicate that UC improved efficiency across the country. Regional hospitals, in particular, improved their efficiency the most. On average, small general hospitals were the most efficient hospitals, followed by large general hospitals and regional hospitals. Comparing the original DEA and the bootstrapping DEA, the result confirms that the bootstrap DEA estimate is the better indication of hospital technical efficiency because of its unbiasedness and consistency.

The Tobit regression shows that the reform is a source of efficiency, which is consistent with the DEA results. Because access of care, especially by those with lower incomes and the uninsured improved, an increase in the number of UC patients per enrollees increased hospital efficiency. This also implies that the capitation budget system which has replaced the incremental financing supply-sided cost, improved efficiency. Considering hospital input allocations, we found that the physicians to other medical staff ratio hurt efficiency before UC, after UC no such effect was evident. An increase in health professional school's capacity may help lessening the shortage of medical personnel in the public health sector.

We found with marginal significance that provinces with more wealth were more efficient relative to those in less wealthy areas. The impact of provincial wealth on efficiency became stronger after UC started in that hospitals in wealthier provinces tended to be more efficient. Considering the effect of number of referrals, the results indicate that more referrals improve efficiency in regional and general hospitals This may be an area for further research. We also found that the Herfindahl index and the presence of private hospitals in the local market, representing degree of competition, do not affect technical efficiency. Finally, we found that the efficiency change depends on geographical locations. Hospitals in the East become the least efficient instead of hospitals in the West after the reform started.

These are very preliminary results, analyzing only at the short-term immediate effects of UC on the efficiency of regional and general hospitals in Thailand. The program implementation is still in the transitional stage. Universal healthcare coverage is still a new concept. In addition, we are able to explain some aspects of hospital efficiency that transcend UC. If the efficiency of regional and general hospitals is considered important, referrals from community hospitals should be encouraged. In addition, we showed regional and income differences in efficiency that may be amenable to policy interventions.

But we stress, once again, that this is a very early and limited analysis since the data are available for only the early years of UC and so likely does not reveal the full impact of how efficiency changed with the reform. Further study, after more time is available for implementation and adjustment, is needed.

Figures

Figure 1: Technical efficiency

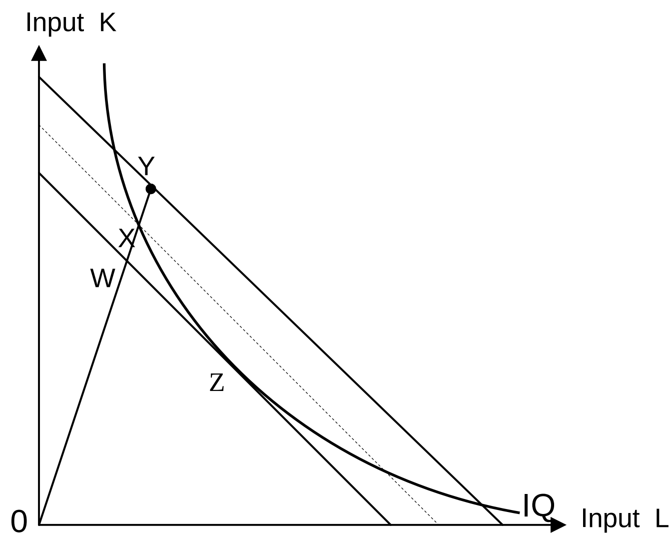

Figure 2: Scale efficiencies

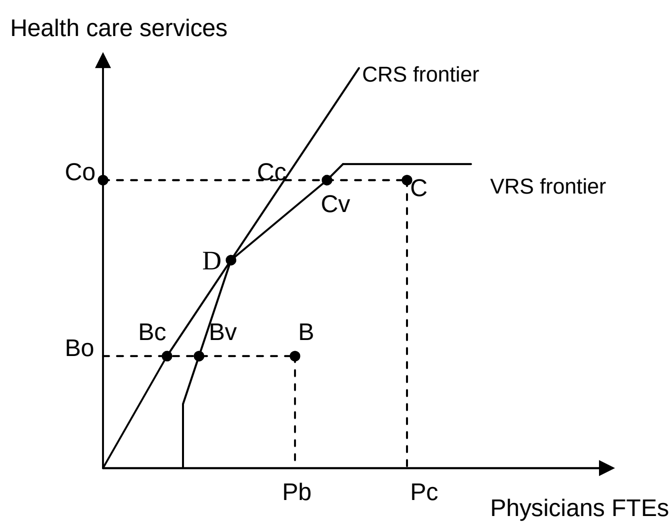

Figure 3: Original DEA and bootstrap DEA efficiency scores

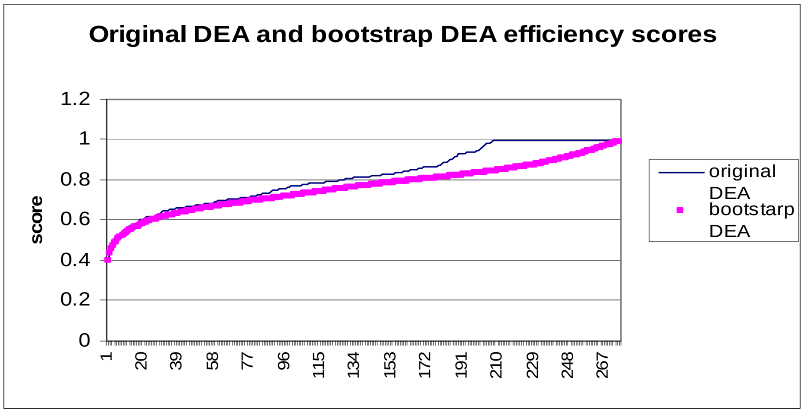

Figure 4: Map of Thailand

Tables

Table 1: Hospital and Medical Establishments with beds by Type of Administration in 2000.

Type of Administration	Number of hospitals	Number of beds
1. Government	939	102,122
- Ministry of Public Health	868	87,752
- Other Ministries	71	14,370
2. State Enterprise	9	2,439
3. Municipality	14	2,279
4. Private	331	29,361
Total	1,293	136,201

Source: Ministry of Public Health

Table 2: Health insurance coverage in Thailand 1991-2003 (%)*

	Before Oct. 2001						**After Oct. 2001**	
Insurance scheme	**1991**	**1992**	**1995**	**1997**	**1999**	**2000**	**Insurance programs**	**2004**
Civil Servant Medical Benefit Scheme (CSMES)	10.2	11.3	11.0	10.8	10.8	12.0	CSMES	8
Social Security Scheme (SSS)*	3.2	4.4	7.3	7.6	9.2	9.4	SSS	13.16
Public Welfare scheme for the poor (PWS)	16.6	35.9	43.9	44.7	42.1	40.8	UC	75.24
Voluntary Health Scheme	2.9	3.9	9.8	15.3	15.8	17.5		
The uninsured	67.1	44.5	28.0	21.6	22.1	20.3	The uninsured	~4

Note : * There were approximately 62.6 millions people in Thailand in 2004.

** Excluded the Workmen Compensation Fund (WCF) and the Car-accident Compensation Scheme, which is considered supplementary schemes where funds are collected from those who are liable for the workplace or traffic accidents.

Source: Health Insurance Systems in Thailand (2001), Health Systems Research Institute, Ministry of Public Health. and The 2004 Universal Coverage Report (2004), National Health Security Office, Ministry of Public Health.

Table 3: Definitions of DEA variables

Variables		Definition
Output	INSUR*	number of adjusted number of inpatient visits in acute surgical – general surgery and Orthopedic surgery
	INPRI*	number of adjusted number of inpatient visits in primary care -- Pediatrics, Medical, and Obstetrics and Gynecology
	INOTHER*	number of adjusted number of inpatient visits in others -- Dental, ENT, Ophthalmology, Rehabilitation medicine, and others
	OUTSUR	number of surgical outpatient visits
	OUTNONSUR	number of non-surgical outpatient visits
Input	BED	Number of beds
	PHYSICIAN	Number of physicians FTEs
	NURSE	Number of nurses
	DENPHAR	Number of dentists and pharmacists
	OTHERS	Number of other personnel

Note : * Adjusted inpatient variables of each group are defined as :

ratio of large surgeries to total surgeries * number of inpatients in acute surgical, or primary care,or others
maximum amount of the numerator

Table 4: Descriptive statistics: mean (standard deviation) per year

	INSUR	INPRI	INOTHER	OUTSUR	OUTNONSUR	BED	PHYSICIAN	NURSE	DENPHAR	OTHERS
2000	6,635.98 (4638.09)	15,316.20 (7233.29)	2,534.59 (3538.75)	3,200.65 (4,299.13)	218,966.4 (101,352.8)	431 (196)	43 (30)	369 (155)	21 (9)	65 (26)
2001	6,338.22 (4367.66)	14,977.59 (7088.26)	2,163.44 (2041.67)	2,986.67 (3,855.13)	222,951.9 (103,369.2)	431 (196)	46 (33)	383 (167)	22 (8)	70 (28)
2002	6,853.25 (4849.56)	15,620.97 (7277.47)	2,166.13 (2794.22)	2,880.45 (3,665.88)	370,325.0 (157,762.8)	439 (201)	50 (38)	404 (176)	24 (10)	78 (34)

Table 5: Definition of explanatory variables

Categories	Variables	Definition
Dependent variables	INEFF	Inefficient scores
Input mix	PHYRATIO	Ratio of FTE physicians to other full-time personnel
	BED	Number of beds
Services	REFER	Number of patients referring from the other hospitals (‘000)
	LOS	Length of stay
Geographic influences	NORTH	1, if from the northern region
	NORTHEAST	1, if from the northeastern region
	CENTRAL	1, if from the central region (exclude Bangkok)
	EAST	1, if from the eastern region
	WEST	1, if from the western region
	SOUTH	1, if from the southern region
	ISLAM	1, if a hospital located in Muslim-dominated provinces
Effect from UC	INUC	Number of UC inpatients/UC enrollees of that hospital (persons)
	OUTUC	Number of UC outpatients/UC enrollees of that hospital (persons)
Market factors	PRIBED	Number of beds in private hospitals of each province
	HI	Herfindahl index
	GPPCR	Real Gross Provincial Product per capita

Table 6: Descriptive statistics of explanatory variables

YEAR	OUTUC	INUC	GPPCR	LOS	BED	PHYRATIO	REFER	HI	PRIBED
2000	0	0	44,226.92	4.91	430.80	0.0802	9,246.10	0.21	244.73
2001	0	0	44,253.32	4.84	430.80	0.0823	9,487.73	0.21	279.07
2002	0.205	0.046	46,931.04	5.06	439.49	0.0831	9,762.28	0.212	313.41

Table 7: Mean technical efficiency in 2000 to 2002 by type of hospitals

Type	2000	2001	2002	Average by type
Regional hospitals	0.729	0.683	0.845	0.753
Large general hospitals	0.835	0.790	0.837	0.821
Small general hospitals	0.898	0.875	0.935	0.903
Average by year	0.829	0.779	0.860	0.819

Table 8: Mean technical efficiency by region

\Region Period	North	Northeast	Central	East	West	South
pre-UC (2000 and 2001)	0.81	0.91	0.76	0.70	0.71	0.80
post-UC (2002)	0.84	0.96	0.81	0.74	0.78	0.91
%change	5%	5.4%	7.4%	5.5%	9.7%	13.4%

Table 9: Number of hospitals experiencing a change in efficiency during 2000-2001, 2001-2002, and 2000-2002

Changes in efficiency	2000 V.S.2002	%	2000 V.S.2001	%	2001 V.S.2002	%
Increase	50	54.3%	25	27.2%	65	70.7%
Unchanged	14	15.2%	8	8.7%	9	9.8%
Decrease	28	30.4%	59	64.1%	18	19.6%

Table 10: Changes in number of surgical and non-surgical outpatient visits in 2000 to 2001 and 2001 to 2002

year	2000-2001					2001-2002			
Type\	Non-surgery					Non-surgery			
	Change in visits (number of hospitals)	Increase	Decrease	Unchanged		Change in visits (number of hospitals)	Increase	Decrease	Unchanged
	Increase	15	13	0		Increase	46	4	0
Surgery	Decrease	33	30	0	Surgery	Decrease	42	0	0
	Unchanged	1	0	0		Unchanged	0	0	0

Table 11: Changes in number of surgical and non-surgical inpatient visits in 2000 to 2001 and 2001 to 2002

year	2000-2001					2001-2002			
Type\	Non-surgery					Non-surgery			
	Change in visits (number of hospitals)	Increase	Decrease	Unchanged		Change in visits (number of hospitals)	Increase	Decrease	Unchanged
	Increase	23	10	0		Increase	48	15	0
Surgery	Decrease	18	41	0	Surgery	Decrease	11	18	0
	Unchanged	0	0	0		Unchanged	0	0	0

Note: Non-surgical inpatient visits consist of INPRI and INOTHER. Surgical inpatient visits are INSUR.

Table 12: Changes in number of health personnel (physicians and other medical staffs) in 2000 to 2001 and 2001 to 2002

year Type\	2000-2001				2001-2002				
	Other staff				Other staff				
	Change in number of health personnel (number of hospitals)	Increase	Decrease	Unchanged		Change in number of health personnel (number of hospitals)	Increase	Decrease	Unchanged
Physicians	Increase	36	13	4	**Physicians**	Increase	46	13	0
	Decrease	14	11	5		Decrease	16	11	1
	Unchanged	5	3	5		Unchanged	5	0	1

Table 13: Kruskal-Wallis test of technical efficiency (original DEA) by year

Test	Value
Chi-Square	14.902
Degree of freedom	2
p-value	.001

Table 14: Pairwise comparisons: Mann-Whitney test

Technical efficiency (DEA efficiency scores)	t-statistics
2000 versus 2001	-1.777*
2001 versus 2002	-3.884***
2000 versus 2002	-2.027**

Note : * = significant at a 0.10 level of significant
** = significant at a 0.05 level of significant
*** = significant at a 0.01 level of significant

Table 15: Number of efficient hospitals (TE = 1): By type and by region

Type	Region	Year			Total
		2000	2001	2002	
Regional hospitals	North	1	-	3	4
	Northeast	3	1	5	9
	Central	-	-	1	1
	East	-	-	-	-
	West	-	-	-	-
	South	-	-	2	2
	Total	4	1	11	16
Large general hospitals	North	3	1	2	6
	Northeast	5	3	7	15
	Central	1	1	2	4
	East	-	-	-	-
	West	-	-	-	-
	South	1	2	1	4
	Total	10	7	12	29
Small general hospitals	North	-	1	1	2
	Northeast	2	1	2	5
	Central	1	-	1	2
	East	1	-	1	2
	West	-	-	1	1
	South	4	3	5	12
	Total	8	5	11	24
All hospitals		22	13	34	69

Table 16 : Efficiency result - Original DEA estimates and bootstrap estimates

	N	Minimum	Maximum	Mean	Std. Deviation
Original DEA scores	276	0.39	1.00	0.8192	0.1450
Bootstrap DEA scores	276	0.40	1.00	0.7633	0.1183

Table 17: Descriptive statistics - Original DEA and bootstrap DEA estimates, 2000-2002

YEAR	Statistics	Original DEA	Bootstrap DEA	BIAS
2000	Mean	0.8193	0.7503	0.069
	Std. Deviation	0.1470	0.1037	0.049
	Minimum	0.47	0.46	0.006
	Maximum	1.00	0.88	0.152
2001	Mean	0.7787	0.7294	0.049
	Std. Deviation	0.1380	0.1088	0.0337
	Minimum	0.39	0.40	-0.013
	Maximum	1.00	0.90	0.148
2002	Mean	0.8596	0.8100	0.0496
	Std. Deviation	0.1399	0.1272	0.030
	Minimum	0.48	0.47	0
	Maximum	1.00	1.00	0.151
Total	Mean	0.8192	0.7633	0.056
	Std. Deviation	0.1450	0.1183	0.039
	Minimum	0.39	0.40	-0.013
	Maximum	1.00	1.00	0.152

Table 18: Likelihood-ratio tests of null hypotheses for parameters of the Tobit model

Null hypothesis	Test statistics, λ	Result	Implication
$H_0 : a^* = 0$	3.98 $(\chi^2_{(0.05,1)} = 3.84)$	Reject	The intercepts of both periods are not equal.
$H_0 : b_i^* = 0$	22.56 $(\chi^2_{(12)} = 21.03)$	Reject	At least one of slope coefficients is not equal to zero.
$H_0 : c = 0$	5.14 $(\chi^2_{(1)} = 3.84)$	Reject	Include the UC variable in the Tobit model.
$H_0 : a^* = b_i^* = c = 0$	54.12 $(\chi^2_{(14)} = 23.68)$	Reject	At least one of the coefficient is not equal to zero.
$H_0 : b_{PHYRATIO} + b^*_{PHYRATIO} = 0$	1.1 $(\chi^2_{(1)} = 3.84)$	Cannot reject	The sum of the coefficients is equal to zero.
$H_0 : b_{GPPCR} + b^*_{GPPCR} = 0$	4.9 $(\chi^2_{(1)} = 3.84)$	Reject	The sum of the coefficients is not equal to zero.

Table 19: Tobit regression result

Variables	Coefficient	Std. Error	t-statistics	p-value
Constant	0.021625	0.1107537	0.2	0.845
OUTUC	-0.48927	0.2042082	-2.4	0.017
BED	5.99E-05	0.0001273	0.47	0.638
GPPCR	-4.49E-07	3.09E-07	-1.45	0.146
LOS	0.039212	0.0157615	2.49	0.013
PHYRATIO	2.263139	0.7021813	3.22	0.001
REFER	-6.32E-06	1.70E-06	-3.71	0
HI	0.232416	0.1984475	1.17	0.242
NORTH	0.025885	0.0436509	0.59	0.553
NORTHEAST	-0.1118	0.047162	-2.37	0.018
CENTRAL	0.087413	0.0479739	1.82	0.068
EAST	0.063152	0.0606847	1.04	0.298
WEST	0.191863	0.0573754	3.34	0.001
ISLAM	0.035815	0.0571966	0.63	0.531
PRIBED	-6.3E-05	0.0000568	-1.11	0.267
D	0.349	0.1742015	2	0.045
D*BED	-0.0001	0.0001735	-0.59	0.555
D*GPPCR	-8.11E-07	5.10E-07	-1.59	0.112
D*LOS	-0.01271	0.0285234	-0.45	0.656
D*PHYRATIO	-2.83071	1.120029	-2.53	0.011
D*REFER	3.07E-06	2.72E-06	1.13	0.258
D*HI	-0.25212	0.3347051	-0.75	0.451
D*NORTH	0.02855	0.0770217	0.37	0.711
D*NORTHEAST	0.03633	0.0803209	0.45	0.651
D*CENTRAL	0.076444	0.0847467	0.9	0.367
D*EAST	0.225565	0.105738	2.13	0.033
D*WEST	0.047963	0.0987488	0.49	0.627
D*ISLAM	-0.12788	0.0993048	-1.29	0.198
D*PRIBED	-1.9E-05	0.0000864	-0.22	0.825
Log likelihood = 102.30				
Likelihood-ratio test of sigma_u=0 (pooled V.S. random effect): Chi-square(1)= 19.50, p-value= 0.000				
Levene Statistic = 2.521 (p-value =0.114)				

Note :
1. The dependent variable = inefficiency score = (1/TE) -1.
2. D is a period dummy variable indicating 1 if post-UC, and 0 if pre-UC.
3. * = significant at a 0.10 level of significant
   ** = significant at a 0.05 level of significant
   *** = significant at a 0.01 level of significant

Appendix

Appendix 1: Descriptive statistics of input and output variables: mean by year and type of hospitals

TYPE	YEAR	INSUR	INPRI	INOTHER	OUTSUR	OUTNONSUR	BED	PHYSICIAN	NURSE	DENPHAR	OTHERS
Regional hospitals	2000	11,504.4	21,905.2	4,303.1	6,374.0	336,922.5	673.6	80.5	561.6	32.3	95.5
	2001	10,895.1	21,235.9	3,678.4	5,750.8	338,280.9	673.6	86.7	592.2	32.8	102.0
	2002	11,663.8	22,138.1	4,524.5	5,665.4	530,429.6	689.4	95.4	619.1	35.0	120.7
	Total	11,354.5	21,759.7	4,168.7	5,930.1	401,877.7	678.9	87.5	591.0	33.4	106.1
Large general hospitals	2000	5,950.0	14,979.0	2,370.0	2,160.1	197,879.9	391.8	33.3	333.8	18.4	60.5
	2001	5,666.0	14,599.3	1,943.2	2,104.5	203,124.6	391.8	34.9	341.3	19.9	64.5
	2002	6,142.9	14,869.7	1,594.5	2,018.8	344,187.0	395.8	38.0	366.4	22.8	70.1
	Total	5,919.6	14,816.0	1,969.2	2,094.5	248,397.2	393.1	35.4	347.2	20.4	65.0
Small general hospitals	2000	1,963.2	7,498.3	623.5	1,654.0	117,032.2	210.1	17.8	202.3	12.2	38.3
	2001	2,040.7	7,698.6	726.5	1,578.2	121,292.9	210.1	19.8	212.5	13.2	41.3
	2002	2,318.1	8,943.8	507.1	1,392.9	225,693.8	221.0	19.3	214.8	12.9	41.1
	Total	2,107.3	8,046.9	619.0	1,541.7	154,673.0	213.7	18.9	209.8	12.8	40.2
Total	2000	6,636.0	15,316.2	2,534.6	3,200.7	218,966.4	430.8	42.9	368.5	20.9	65.4
	2001	6,338.2	14,977.6	2,163.4	2,986.7	222,951.9	430.8	45.9	382.9	22.0	69.9
	2002	6,853.3	15,621.0	2,166.1	2,880.5	370,325.0	439.5	49.7	403.8	24.0	77.8
	Total	6,609.1	15,304.9	2,288.1	3,022.6	270,747.7	433.7	46.2	385.1	22.3	71.0

Appendix 2: Descriptive statistics of input and output variables: mean by year and location of hospitals

RELIGION	YEAR	INSUR	INPRI	INOTHER	OUTSUR	OUTNONSUR	BED	PHYSICIAN	NURSE	DENPHAR	OTHERS
North	2000	7,381.4	15,703.4	3,132.2	3,600.9	216,926.0	446.9	41.2	374.6	22.1	68.5
	2001	6,646.9	14,452.3	2,721.6	3,515.8	217,247.2	446.9	44.1	400.7	22.5	74.9
	2002	7,527.9	14,168.4	2,652.8	3,094.6	392,024.7	455.7	51.5	416.9	26.5	83.7
	Total	7,185.4	14,774.7	2,835.5	3,403.8	275,399.3	449.8	45.6	397.4	23.7	75.7
Northeast-tern	2000	9,548.3	19,879.2	5,124.3	5,334.3	244,051.0	519.3	48.6	403.8	22.3	66.1
	2001	9,006.3	19,040.7	3,390.0	4,608.2	247,684.4	519.3	52.4	414.5	24.9	71.8
	2002	10,106.7	20,084.9	3,212.7	4,734.7	409,618.1	522.7	57.8	446.6	27.3	85.5
	Total	9,553.8	19,668.3	3,909.0	4,892.4	300,451.2	520.4	52.9	421.6	24.8	74.5
Central	2000	4,979.7	13,767.9	1,172.1	2,109.0	222,394.9	375.3	38.9	347.1	19.7	63.7
	2001	4,768.5	13,116.5	1,218.5	1,878.2	234,652.6	375.3	42.3	355.7	21.3	66.9
	2002	5,071.4	13,998.5	1,613.8	1,758.6	385,393.4	386.2	44.6	381.8	22.5	71.4
	Total	4,939.9	13,627.6	1,334.8	1,915.3	280,813.6	378.9	41.9	361.5	21.2	67.3
East	2000	7,296.4	16,101.6	1,981.4	2,232.3	234,033.4	499.0	68.0	433.4	24.7	75.6
	2001	7,756.4	16,694.0	2,384.7	1,997.4	244,059.1	499.0	70.1	431.7	23.3	80.4
	2002	7,300.2	17,246.8	2,034.4	1,984.7	382,859.7	526.3	72.4	454.6	25.3	93.4
	Total	7,451.0	16,680.8	2,133.5	2,071.5	286,984.1	508.1	70.2	439.9	24.4	83.1
West	2000	4,866.6	12,124.8	1,190.1	2,677.5	186,946.1	400.3	39.6	330.5	19.1	59.1
	2001	4,477.0	11,824.5	1,302.7	3,174.0	187,704.8	400.3	41.9	335.5	21.3	62.5
	2002	4,324.7	11,711.8	1,294.6	3,014.8	311,606.6	406.5	44.0	356.3	21.4	64.5
	Total	4,556.1	11,887.0	1,262.5	2,955.4	228,752.5	402.3	41.8	340.8	20.6	62.0
South	2000	5,097.0	12,948.2	1,448.2	2,314.4	200,532.3	368.7	35.3	340.5	18.9	62.2
	2001	5,176.1	14,023.8	1,575.2	2,202.3	199,588.1	368.7	37.5	361.8	19.3	64.9
	2002	5,571.4	15,355.5	1,575.1	2,196.0	313,227.2	374.5	39.0	370.2	20.5	70.3
	Total	5,281.5	14,109.2	1,532.8	2,237.6	237,782.5	370.6	37.2	357.5	19.5	65.8
Total	2000	6,636.0	15,316.2	2,534.6	3,200.7	218,966.4	430.8	42.9	368.5	20.9	65.4
	2001	6,338.2	14,977.6	2,163.4	2,986.7	222,951.9	430.8	45.9	382.9	22.0	69.9
	2002	6,853.3	15,621.0	2,166.1	2,880.5	370,325.0	439.5	49.7	403.8	24.0	77.8
	Total	6,609.1	15,304.9	2,288.1	3,022.6	270,747.7	433.7	46.2	385.1	22.3	71.0

Appendix 3: Descriptive statistics of explanatory variables: mean by type and location

Type	Region	OUTUC	INUC	GPPCR*	LOS	PHYRATIO	REFER	PRIBED	HI
Regional hospitals	North	0.21	0.06	23,809.07	5.53	0.10	29,533.20	435.50	0.24
	Northeast	0.30	0.09	17,567.98	5.21	0.11	28,155.00	399.50	0.14
	Central	0.17	0.04	96,184.65	5.49	0.10	8,488.25	371.75	0.19
	East	0.13	0.04	135,105.06	5.67	0.12	9,785.92	391.38	0.23
	West	0.09	0.05	47,163.82	5.84	0.12	10,404.67	405.50	0.15
	South	0.24	0.04	35,486.19	5.30	0.09	15,198.73	319.00	0.19
	Total	0.21	0.06	54,968.28	5.44	0.10	19,043.64	385.10	0.19
Large general hospitals	North	0.18	0.04	25,094.41	4.63	0.07	9,558.56	257.62	0.21
	Northeast	0.20	0.04	14,047.34	4.51	0.07	9,265.88	85.82	0.20
	Central	0.15	0.04	80,443.19	5.15	0.08	3,267.58	533.73	0.21
	East	0.18	0.05	57,673.67	5.24	0.08	4,217.67	156.50	0.30
	West	0.33	0.04	43,747.51	5.18	0.08	3,696.67	358.25	0.16
	South	0.17	0.04	39,948.94	4.88	0.07	5,094.49	179.57	0.24
	Total	0.19	0.04	40,325.06	4.83	0.08	6,687.77	274.31	0.21
Small general hospitals	North	0.12	0.02	16,361.53	4.21	0.06	3,356.50	50.00	0.25
	Northeast	0.46	0.04	10,328.20	4.17	0.07	19,426.17	72.50	0.28
	Central	0.17	0.03	98,391.75	5.19	0.07	1,428.50	299.13	0.17
	East	0.42	0.05	20,691.18	4.16	0.10	3,128.33	0.00	0.23
	West	0.16	0.04	42,192.42	4.67	0.08	2,801.11	288.67	0.13
	South	0.23	0.05	35,512.55	4.39	0.06	1,995.14	81.79	0.29
	Total	0.23	0.04	44,358.04	4.55	0.07	4,040.89	151.58	0.23
All hospitals	North	0.18	0.04	23,899.79	4.82	0.08	13,932.02	281.33	0.22
	Northeast	0.26	0.06	14,767.63	4.69	0.08	16,300.37	183.47	0.19
	Central	0.16	0.04	87,535.83	5.23	0.08	3,979.49	450.24	0.20
	East	0.19	0.04	96,636.97	5.33	0.11	7,243.90	268.36	0.25
	West	0.24	0.04	43,591.39	5.07	0.08	4,199.33	338.06	0.15
	South	0.21	0.05	37,140.07	4.81	0.07	6,611.64	180.24	0.25
	Total	0.20	0.05	45,137.10	4.94	0.08	9,498.70	279.07	0.21

Note: * The value is at a constant term of 1988.

Appendix 4: Chronology

Fiscal year	Month	Important events
2000	Oct. 1999 .. .. Sep. 2000	
2001	Oct. 2000 .. January Feb, 2001 March April … September, 2001	Thai Rak Thai party had a victory on the general election. UC has started in 6 out of 76 provinces,
2002	October, 2001 November … April, 2002 .. September, 2002	UC was implemented to most provinces except Bangkok. UC was fully implemented.

Appendix 5: Number of efficient hospitals (TE = 1) : By region and by type

Region	Type of hospitals	YEAR			Total
		2000	2001	2002	
North	Regional hospitals	1	-	3	4
	Large general hospitals	3	1	2	6
	Small general hospitals	-	1	1	2
	Total	4	2	6	12
Northeast	Regional hospitals	3	1	5	9
	Large general hospitals	5	3	7	15
	Small general hospitals	2	1	2	5
	Total	10	5	14	29
Central	Regional hospitals	-	-	1	1
	Large general hospitals	1	1	2	4
	Small general hospitals	1	-	1	2
	Total	2	1	4	7
East	Regional hospitals	-	-	-	-
	Large general hospitals	-	-	-	-
	Small general hospitals	1	-	1	2
	Total	1	-	1	2
West	Regional hospitals	-	-	-	-
	Large general hospitals	-	-	-	-
	Small general hospitals	-	-	1	1
	Total	-	-	1	1
South	Regional hospitals	-	-	2	2
	Large general hospitals	1	2	1	4
	Small general hospitals	4	3	5	12
	Total	5	5	8	18
TOTAL		22	13	34	69

Appendix 6: Algorithm (applied from Bodin and Simar 2003)

Step 1). Find the original efficiency estimates. For each observed producer $(x_i, y_i) \in \chi_n$, compute the DEA estimator of the efficiency score $\hat{\theta}_i = \hat{\theta}_{DEA}(x_i, y_i)$, i = 1, ..., n.

Step 2). If $(x_0, y_0) \notin \chi_n$ repeat step 1) for (x_0, y_0) to obtain $\hat{\theta}_i = \hat{\theta}_{DEA}(x_0, y_0)$.

Step 3). Define $S_m = \{\hat{\theta}_1, ..., \hat{\theta}_m\}$ where m = # $\{\hat{\theta}_i < 1\}_{1 \le i \le n}$, i.e. the number of inefficient producers.

Step 4). Giving n is the number of decision-making units (DMUs), estimate $f(\hat{\theta})$ from the remaining $\hat{\theta}$ and generate B samples of the boundary condition $\hat{\theta} < 1$ (the size n-1), which is $\{\hat{\theta}_1^{*b}, ..., \hat{\theta}_{n-1}^{*b}.\}_{b=1}^{B}$. The steps are as follows:

4.1). Given a random sample $x_1, ..., x_n$ with a continuous, univariate density f, the kernel density estimator is defined by:[19]

$$\hat{f}(z) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \qquad \text{(a1)}$$

where $K(\cdot)$ is the kernel function and h is the bandwidth parameter. Under mild conditions (h must decrease with increasing n) the kernel estimate converges in probability to the true density. Performance of kernel is measured by MISE (mean integrated squared error).

Bandwidth selection is a crucial issue in the application of the smoothing procedure. Refer to Silverman (1986) for a completed review of several approaches of bandwidth selection. In this paper, the bandwidth function rule for univariate data recommended by silverman (1986, eq.3.31) is

$$h = 0.9\left(\min\begin{cases}\hat{\sigma}_{\hat{\theta}} \\ R_{13}/1.34\end{cases}\right) n^{-1/5}$$

where R_{13} denotes the inter-quartile range of the sample $\{\hat{\theta}_i\}$ and denotes the standard deviation estimate of the efficiency estimates $\{\hat{\theta}_i\}$, respectively.[20]

4.2). Using the reflection method (Silverman,1986), we estimate $f(\hat{\theta})$ under the boundary condition $\hat{\theta} < 1$. Suppose we have m inefficient producers, denoting $S_m = \{\hat{\theta}_1, ..., \hat{\theta}_m\}$. In order to find a consistent estimator of $f(\hat{\theta})$, let $\{\beta_1^*, ..., \beta_{n-1}^*\}$ be a bootstrap sample, obtained by sampling with replacement from S_m and $\{\varepsilon_1^*, ..., \varepsilon_{n-1}^*\}$ a random variable of standard normal deviates. By the convolution formula, we have

[19] *Kernel density estimation* is a nonparametric technique for density estimation in which a known density function (the *kernel*) is averaged across the observed data points to create a smooth approximation. Usually, the kernel function is a probability density function, symmetric around zero.

[20] The choice of smoothing variable is chosen because Silverman (1986) suggested that it copes very well for a wide range of densities; both unimodal densities and moderately bimodal densities.

$$\tilde{\theta}_i^* = \beta_i^* + h\varepsilon_i^* \sim \frac{1}{m}\sum_{j=1}^{m}\frac{1}{h}\phi\left(\frac{z-\hat{\theta}_{(j)}}{h}\right)$$

for i = 1,…,n-1. Define now for i = 1,….,n-1 the bootstrap data:

$$\theta_i^* = \begin{cases} \tilde{\theta}_i^* & if\ \tilde{\theta}_i^* < 1 \\ 2-\tilde{\theta}_i^* & otherwise. \end{cases} \tag{a2}$$

where θ_i^* defined in (a2) is proved to be random variables distributed according to $\hat{f}_h(z)$. The final smoothed resample efficiencies are obtained by rescaling the bootstrap data making the variance is approximately the sample variance of $\hat{\theta}_i$. We employ the following transform:

$$\hat{\theta}_i^* = \bar{\hat{\theta}} + \frac{1}{\sqrt{(1+h^2/\hat{\sigma}^2)}}(\theta_i^* - \bar{\hat{\theta}}),$$

where $\bar{\hat{\theta}} = \frac{1}{n}\sum_{j=1}^{n}\hat{\theta}_j$ and $\hat{\theta}^2 = \frac{1}{n}\sum_{j=1}^{n}(\hat{\theta}_j - \bar{\hat{\theta}})^2$.

Step 5). Then, draw n-1 bootstrap values $\hat{\theta}_i^*$, i = 1,….,n-1 from the kernel density estimate of $f(\hat{\theta})$ and sort in ascending order: $\hat{\theta}_{(1)}^* \leq ... \leq \hat{\theta}_{(n-1)}^*$.

Step 6). Repeat step 5 (drawing n-1 bootstrap values $\hat{\theta}_i^*$) B times (in this study, 1000 times), to obtain a set of B bootstrap estimates $\{\hat{\theta}_{(n-j)}^{*b}\}_{b=1}^{B}$, for some $1 \leq j \leq n-1$.[21]

Step 7). Finally, approximate $\tilde{\theta}_{(n-j)}$ for some j $(1 \leq j \leq n-1)$ by the average of $\hat{\theta}_{(n-j)}^{*b}$ over the B simulations (in this study, 1000 times):

$$\tilde{\theta}_{(n-j)} = \frac{1}{B}\sum_{b=1}^{B}\hat{\theta}_{(n-j)}^{*b} \tag{a3}$$

21 Replications is set to B = 1000. Efron and Tibshirani (1993), p.275, recommend at least this number of simulation replicates in order to make the variability of the boundaries of the bootstrap confidence intervals “acceptably” low.

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