

ประสิทธิภาพของโรงพยาบาลจิตเวช กระทรวงสาธารณสุข



นางสาวพิมพ์นิตา กุลสุนทราลัย

ศูนย์วิทยุทรัพยากร
วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
จุฬาลงกรณ์มหาวิทยาลัย
สาขาวิชาเศรษฐศาสตร์สาธารณสุข

คณะเศรษฐศาสตร์ จุฬาลงกรณ์มหาวิทยาลัย

ปีการศึกษา 2553

ลิขสิทธิ์ของจุฬาลงกรณ์มหาวิทยาลัย

EFFICIENCY OF PSYCHIATRIC HOSPITALS UNDER MINISTRY OF PUBLIC HEALTH

Miss Pimnida Koolsoontralai

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science Program in Health Economics

Faculty of Economics

Chulalongkorn University

Academic Year 2010

Copyright of Chulalongkorn University

พิมพ์นิตดา กุลสุนทราลัย : ประสิทธิภาพของโรงพยาบาลจิตเวช กระทรวงสาธารณสุข.
(EFFICIENCY OF PSYCHIATRIC HOSPITALS UNDER MINISTRY OF PUBLIC
HEALTH) อ. ที่ปรึกษาวิทยานิพนธ์หลัก: รศ.ดร. โสคติธร มัลลิกะมาส,อ. ที่ปรึกษา
วิทยานิพนธ์ร่วม นพ. อภิชัย มงคล 77 หน้า.

การศึกษานี้มีวัตถุประสงค์เพื่อศึกษาประสิทธิภาพโรงพยาบาลจิตเวช กระทรวง
สาธารณสุข และปัจจัยที่มีผลต่อประสิทธิภาพ โดยใช้เทคนิคการวิเคราะห์แบบ DEA และ
ข้อมูลโรงพยาบาลจิตเวช กระทรวงสาธารณสุข จำนวน 16 แห่ง (64 ข้อมูล) ตั้งแต่ปี พ.ศ.
2550 ถึง พ.ศ.2553 โดยตัวแปรของปัจจัยการผลิต คือ จำนวนบุคลากร และจำนวนเตียง ตัว
แปรของผลผลิต คือ จำนวนครั้งของการเข้ารับบริการของผู้ป่วยนอก จำนวนวันรับการ
รักษาของผู้ป่วยใน และจำนวนของผู้ผ่านการอบรมเฉพาะทางทางพยาบาลจิตเวช

ผลการศึกษาพบว่าโรงพยาบาล มี ค่าเฉลี่ยประสิทธิภาพทางเทคนิคที่แท้จริง ร้อยละ
84(ต่ำสุดร้อยละ 42) ค่าประสิทธิภาพต่อขนาด เฉลี่ยร้อยละ 85 (ต่ำสุดร้อยละ 46) การที่ไม่มี
ประสิทธิภาพทางขนาดของโรงพยาบาลส่วนใหญ่เป็นแบบผลตอบแทนที่ลดลง จากการ
วิเคราะห์โดยเทคนิคสมการถดถอยพบว่าจำนวนผู้ป่วยนอกต่อบุคลากร จำนวนผู้ป่วยในต่อ
จำนวนเตียง จำนวนวันนอนเฉลี่ย และการจัดอบรมหลักสูตรการพยาบาลเฉพาะทาง มี
ความสัมพันธ์เชิงบวกกับคะแนนประสิทธิภาพ

การวิจัยครั้งนี้เสนอแนะให้มีการกำหนดทิศทางนโยบาย โดย เน้นการปรับปรุงการ
จัดสรรอัตรากำลังและปรับลดขนาดของโรงพยาบาลบางแห่ง การพัฒนาการให้บริการโดย
เน้นการส่งเสริมและสนับสนุนให้มีงานบริการผู้ป่วยนอกเชิงรุก และการพัฒนาศักยภาพ
โรงพยาบาลให้มีอบรมหลักสูตรการพยาบาลเฉพาะทาง

สาขาวิชาเศรษฐศาสตร์สาธารณสุข
ปีการศึกษา 2553

ลายมือชื่อนิตดา.....
ลายมือชื่อ อ.ที่ปรึกษาวิทยานิพนธ์หลัก.....
ลายมือชื่อ อ.ที่ปรึกษาวิทยานิพนธ์ร่วม.....

5085696229 : MAJOR HEALTH ECONOMICS

KEYWORDS : EFFICIENCY /PSYCHIATRIC HOSPITAL / DEA / REGRESSION

PIMNIDA KOOLSOONTRALAI: EFFICIENCY OF PSYCHIATRIC HOSPITAL
UNDER MINISTRY OF PUBLIC HEALTH. ADVISOR : ASSOC. PROF.
SOTHITHORN MALLIKAMAS, Ph.D., CO-ADVISOR : APICHAJ MONGKOL
M.D., 77 pp.

The objective of this study was to measure the hospital efficiency of psychiatric hospitals under the Department of Mental Health in Thailand in terms of technical and scale efficiency scores and to identify the factors determining the efficiency of hospitals. The data were from sixteen psychiatric hospitals under the Department of Mental Health since 2007 to 2010. The input variables were number of all staff (STAFF) and number of beds (BED) and the output variables were number of out-patient visits (OPD), number of in-patient bed days (IPD), and number of psychiatric nurse trainee (TRAIN).

The results of DEA showed that TEVRS or pure technical efficiency score was 84% average (minimum 42%) and scale efficiency score was 85% (minimum 46%). Decreasing returns to scale is the majority cause of scale inefficiency. The regression analysis results showed OPD/STAFF, IPD/BED, average length of stay and psychiatric nurse trainee activity had significant positive relationship with TEVRS.

The results suggested for downscaling and re-allocation of inputs. Promotion and support the development of proactive outpatient services were recommended. In addition, we should focus more on capacity building of nurse training program in more hospital

Field of Study : Health Economics

Academic Year : 2010

Student's Signature *Pimnida*
Advisor's Signature *S. Thit. M. K.*
Co-advisor's Signature *Apichai*

Acknowledgements

I would like to take this opportunity to express my profound gratitude to all those who kindly cooperated in the completion of the thesis. My first must go to my committee at Chulalongkorn University, Faculty of Economics, Center for Health Economics, Apichai Mongkol, MD, Associate Professor Sothithorn Mallikamas, PhD, Associate Professor Siripen Supakankunti, PhD, Associate Professor Buranee KanChanatawan, MD, and Associate Professor Wattana Suwanseang Junjareon, PhD for their help and comments that improved various parts of the thesis.

I am hugely indebted to Associate Professor Sothithorn Mallikamas, PhD and Associate Professor Siripen Supakankunti, PhD, who kindly advised and gave me a great help to complete my thesis and graduation, many thanks to his and her excellent guidance and support.

I am so grateful to Dr. Apichai Mongkol, Director General of Mental Health Department, who kindly gave me a great chance, excellent guidance and support. I would like to express my special thanks to Dr. Tawee Tungsee and Dr. Prapat Ukranan, my boss for their kindly support to me.

I would like to express my special thanks to Centre for Health Economics professors and staffs especially Mrs. Kingthong Gonganoi for their professional, warm guidance and support. I would like to thank my colleague and friends their support to me.

Thanks to my mom, my warm family and Mr. Peerapol Raungjit my husband for always supported and encourage me.

Contents

	Page
Abstract (Thai)	iv
Abstract (English).....	v
Acknowledgements.....	vi
Contents.....	vii
List of abbreviations	ix
 Chapter I Introduction	
1.1 Problem and its significance.....	1
1.2 Research questions.....	2
1.3 Research objectives.....	3
1.4 Scope of the study.....	3
1.5 Benefit of this study.....	3
 Chapter II Literature review	
2.1 Mental Health in Thailand	5
2.2 Concept of efficiency measurement	11
2.3The Previous Studies.....	32
 Chapter III Methodology	
3.1 Type of data	46
3.2 DEA specification.....	48
3.3 Regression analysis specification	49

	Page
Chapter IV Result and discussion	
4.1 Descriptive statistic analysis.....	52
4.2 Technical efficiency analysis.....	57
4.3 Regression analysis.....	63
4.4 Discussion.....	65
Chapter V Conclusion and recommendation	
5.1 Conclusion.....	69
5.2 Limitation of this study.....	72
5.3 Recommendation.....	72
References.....	73
Biography	77



 ศูนย์วิทยทรัพยากร
 จุฬาลงกรณ์มหาวิทยาลัย

LIST OF ABBREVIATIONS

DEA	Data envelopment analysis
CRS	Constant return to scale
VRS	Variable return to scale
SE	Scale efficiency
TE	Technical efficiency
DRS	Decreasing return to scale
IRS	Increasing return to scale
ALOS	Average length of stay
TECRS	Technical efficiency score under constant returns to scale model
TEVRS	Technical efficiency score under variable returns to scale model



ศูนย์วิจัยทรัพยากร
จุฬาลงกรณ์มหาวิทยาลัย

CHAPTER I

INTRODUCTION

1.1 Problem and Significance

During the past decade health care systems have been under increasing pressure to improve performance to guarantee high quality services and better access to care. Improving Health care performance is important because they can boost the well being as well as standard lining and the economic growth. The quest for high performance in health care has been difficult and intractable problem.

The Department of Mental Health (DMH) is the national mental health authority working under ministry of public health. DMH is responsible for the national mental health policy and strategic planning that aims to develop positive mental health for all Thai people. The some important components of the strategic plans (2007-2011) are developing quality mental health care in public health services and specialized care in psychiatric hospitals/institutes and developing efficient organization in management and human resources.

The data of mental health human resources in 2005 showed scarce the mental health personnel. The psychiatrist to population ratio stands at 0.7 per 100,000 populations, but more than half of the total psychiatrists are located in the capital city, Bangkok. The ratio of psychiatric nurses to population is 3.0 per 100,000 populations. Due to limited resources, the solutions to solve this problem is how to use resources at the most efficient way.

There are many techniques have been used to evaluate the hospital efficiency score. Data Envelopment Analysis, or DEA, is the most popular technique which uses the concept of linear programming to evaluate the efficiency score of many businesses. Besides its powerful characteristics of non-parametric technique which can handle multiple inputs and outputs model. Therefore the data envelopment analysis is a quick tool to estimate for the efficiency score.

There were some studies of hospital efficiency using DEA, but there were a few studies of psychiatric hospitals. So, this study focuses on evaluation of psychiatric hospitals to provide evidence of the technical efficiency score of the hospitals by using DEA. But the efficiency score of using the data envelopment analysis cannot be clarified the factors determining the hospital efficiency scores.

The regression analysis is based on statistical testing and estimation, so this technique can provide more detail in each factor that influences the efficiency score. Therefore, to provide evidence of the technical efficiency score and identify the factors determining the efficiency scores of the psychiatric hospitals. This study used DEA together with regression analysis to find out the direction to improve the technical efficiency.

1.2 Research question

The questions that want to know at present among several problems mentioned are as follows:

1) What level are technical efficiency scores of psychiatric hospitals under the Ministry of Public Health?

2) What are the factors determining their efficiency?

1.3 Research objectives

1) To measure the hospital efficiency of psychiatric hospitals under the Department of Mental Health in Thailand in terms of pure technical efficiency and scale efficiency scores

2) To identify the factors determining the efficiency score of hospitals

1.4 Scope of the study

This is an empirical study using the secondary source of panel data of fiscal year 2007 and 2010. The study covers the entire population of all psychiatric hospitals under the Department of Mental Health, Ministry of Public Health (MoPH) in Thailand. They are composed of 12 psychiatric hospitals, 4 mental health institutes.

1.5 Benefit of this study

This study allow us know the hospital efficiency performance of psychiatric hospitals under the Department of Mental Health in Thailand. The result of this study is useful for

1) Improving organization by using this evidence base as a tool to develop the internal management and monitoring system. The inefficient organization can learn from their best peers by observing their production process or benchmarking. Also by using regression analysis results, the variables determining technical efficiency to find the direction for improvement.

2) For future planning and policy implication, the policy makers can use the result as a guideline in decision making of health resource allocation or reallocation. The target

of input reduction and input slacks of individual hospitals. In addition, the policy makers also use this information to formulate policy direction in organization that which hospital should be downsized or upsized if it is scale inefficiency.



ศูนย์วิจัยทรัพยากร
จุฬาลงกรณ์มหาวิทยาลัย

CHAPTER II

LITERATURE REVIEWS

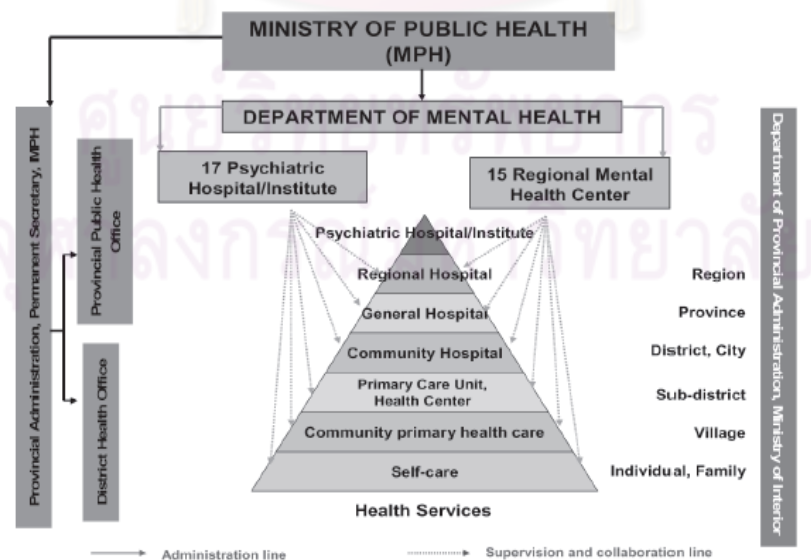
This chapter shows the literature reviews in this study. The following in this chapter is divided into 4 sections. Section 2.1 explains about Mental Health in Thailand. Section 2.2 tells about Concept of efficiency measurement. Section 2.3 explains about the regression analysis and the last section 2.4 tells about the previous studies.

2.1 Mental Health in Thailand

2.1.1 Mental Health Facilities and Services

The mental health services in Thailand are integrated into the public health service system throughout the Ministry of Public Health infrastructure according to the administrative level from the village to regional levels as shown in Figure 2.1 below

Figure 2.1: The Health service system in Thailand



The 17 psychiatric hospitals/institutes shown in figure 2.3 operated by the DMH are distributed throughout the country. They provide specialized psychiatric services for inpatients, outpatients, and chronic rehabilitation services, and there is one specialized service for forensic psychiatry. The total bed numbers is 8,700, which is 13.8 beds per 100,000 populations with 9% reserved for children and adolescents.

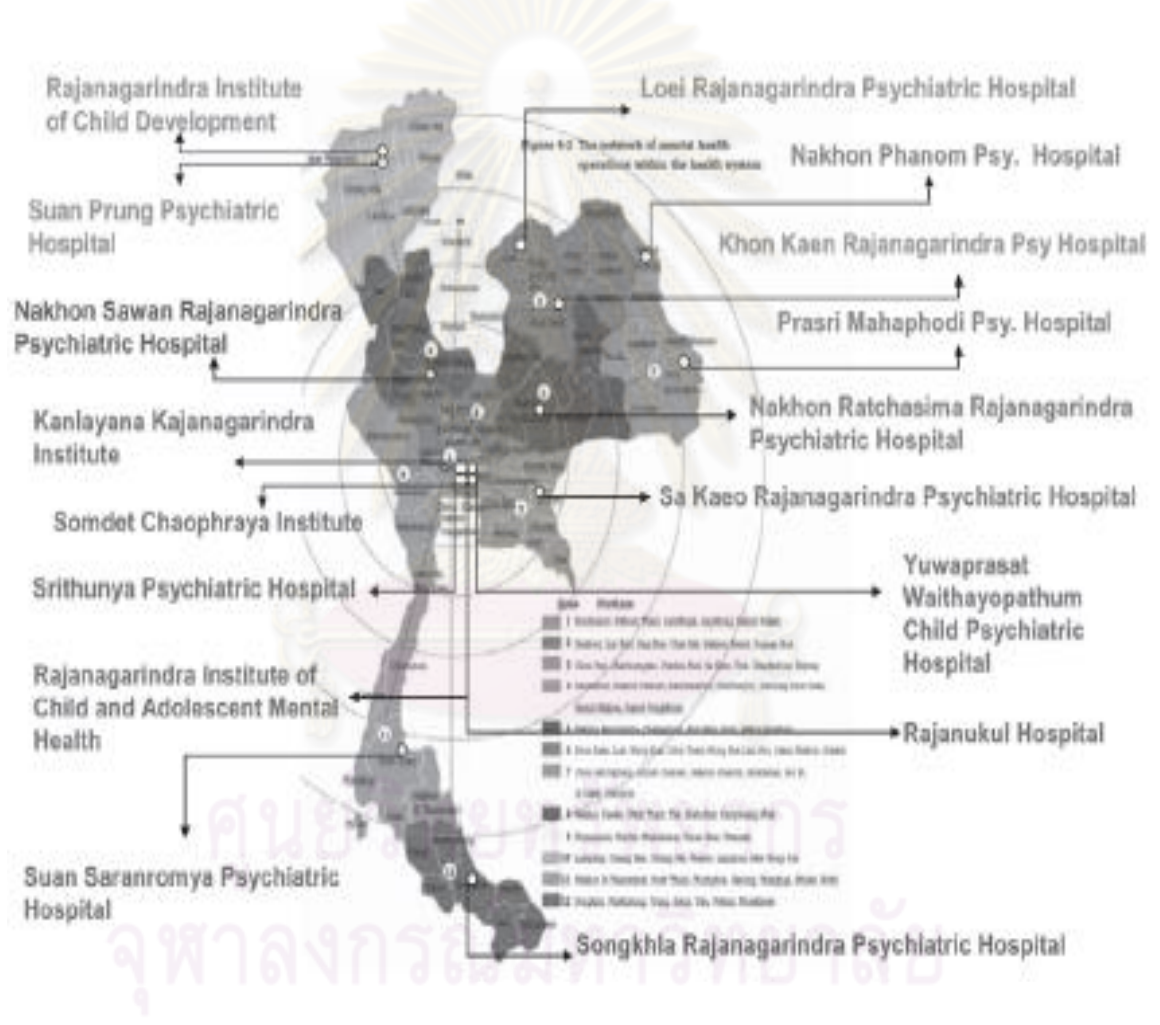


Figure 2.2 The 17 psychiatric hospitals/institutes in Thailand

The mental health center (MHC) shown in figure 2.3 has been established to provide mental health promotion and prevention knowledge to public health care personnel. They have been extended to cover the regional and general hospitals.



Figure 2.3 The mental health centers (MHC) in Thailand

2.1.2 Mental Health Strategy and Principle

DMH, as a government organization, is responsible for the national mental health policy and strategic planning that aims to develop positive mental health for all Thai people. The components of the strategic plans (2007-2011) are as follows:

1. Strengthening the mental health capacity of the population, improving mental health services accessibility and decreasing discrimination of mentally ill people
2. Building and strengthening the mental health network within and outside public health service system
3. Developing organization in mental health expertise through knowledge and research management
4. Developing quality mental health care in public health services and specialized care in psychiatric hospitals/institutes
5. Developing efficient organization in management and human resources.

2.1.3 Mental Health Policy

The Mental Health Policy was initially formulated in 1995 after the reorganization of the “Division of Mental Health in Department of Medical Services” to the “Department of Mental Health (DMH)” under the Ministry of Public Health (MoPH). The policy aims to promote mental health, to prevent mental health problems and to provide the accessibility to quality mental health care through both treatment and rehabilitation that is integrated into public health care. The strategies focus on 1) academic and technical development through research and knowledge management 2) distribution and empowerment of integrated mental health care into public health system as well as mental health network 3) development of mental health personnel and 4) reforming the organization management

system. The mental health strategic plan was last revised in 2007. The mental health legislation has been enforced since 2008.

2.1.4 Mental Health Funding Model

As for budget allocations for mental health, approximately 3.8% of total government health care expenditure was directed to DMH as shown in Figure 2.4. The national universal coverage supports mental health care costs for all care levels along with the referral system; these include the psychotropic drugs in essential drug lists, outpatient and admission costs.

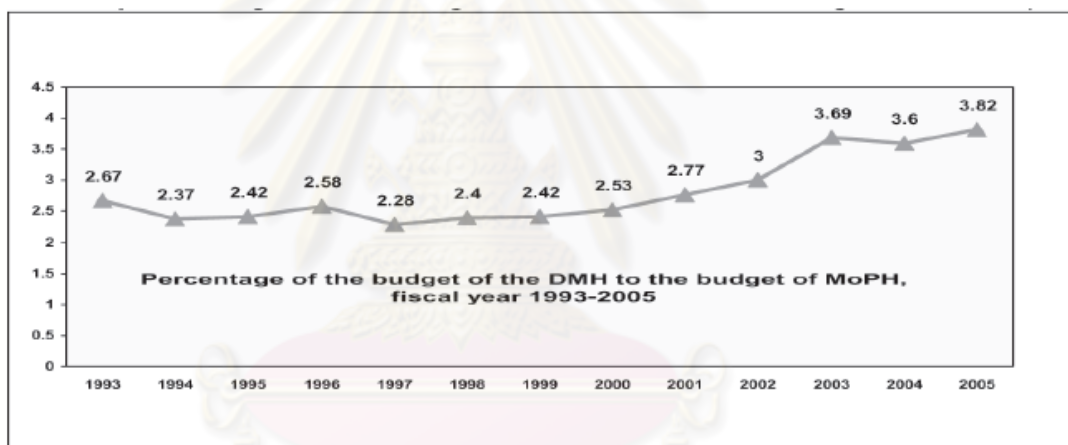


Figure 2.4: The percentage of the budget of the DMH to the budget of MoPH (1993-2005)

2.1.5 Mental Health Workforce and Training system

2.1.5.1 Psychiatrists and medical doctors

- a. The psychiatrist to population ratio stands at 0.7 per 100,000 populations, but more than half of the total psychiatrists are located in the capital city, Bangkok. Graduate medical students are trained for another 3 years before emerging as certified psychiatrists after passing an exit examination conducted by the Royal College of Psychiatrists of Thailand.

- b. Child and adolescent psychiatrists need 4 years of specialized training after medical graduation and an exit examination.
- c. Preventive medicine specialists on community mental health are senior medical doctors who have experience in CMH care for at least 5 years and have completed short course training and an exit examination. Their roles are more focused on promotion and prevention in CMH.
- d. General medical doctors (GP) have 6 years of medical school training in its curriculum plus 1 year of internship.

Table 2.1 Human resources for mental health (2005)

Human Resources	Number	Density (per100,000 population)
Psychiatrist	445	0.7
Psychiatric Nurse	1,868	3.0
Psychologist	230	0.4
Social Worker	214	0.3
Occupational therapist	56	0.09

2.1.5.2 Psychiatric nurses

The ratio of psychiatric nurses to population is 3.0 per 100,000 populations. Nursing training courses include a Master Degree (2 years) in mental health nursing, or an advance diploma (at least 4 months) in mental health or in child and adolescent mental health nursing.

2.1.5.3 Psychologists

The number of clinical psychologists per 100,000 populations is 0.4. Their qualification is a 4 year bachelor degree but certification and registration is needed if they are to engage in clinical practice.

2.1.5.4 Social workers

The ratio of social worker to population is 0.3 per 100,000 populations. Qualified bachelor degree social workers perform not only the social work duties, but also the therapy and rehabilitation.

2.1.5.5 Occupational therapists (OT)

There are only a total of 56 occupational therapists. Qualification requires 4 years for bachelor degree plus certification and registration. OTs are engaged in rehabilitation of both sub-acute and chronic patients.

2.1.6 Accreditation System

All hospitals/institutes have to improve service quality according to the standards set by the Institute of Hospital Quality Improvement and Accreditation under the MoPH which is called Hospital Accreditation (HA) and Health Promotion Hospital (HPH). Mental health is one of the domains evaluated in HA and HPH.

2.1.7 Role of Private Hospital/Providers

Mental health services are largely provided by the MoPH. Only one existing private psychiatric hospital has been operating since 2007. Some private general hospitals have part-time or full time psychiatrists on duty.

2.2 Concept of efficiency measurement

Modern efficiency measurement begins with Farrell (1957) who drew upon the work of Debreu (1951) and Koopmans (1951) to define a simple measure of firm efficiency which could account for multiple inputs. He proposed that the productive efficiency of a firm composes of 2 aspects, technical efficiency or TE and allocative efficiency or AE.

The technical efficiency refers to the use of productive resources in the most technologically efficient manner. It implies the maximum possible output from a given set of inputs or, in reverse, minimum possible input from a given set of outputs. Then TE refers to the physical relationship between the resources used - capital, labor and equipment, and some health outcome. For the outcomes, may either be defined in terms of intermediate outputs or final health outcome.

The allocative efficiency reflects the ability of an organization to use these inputs in optimal proportions, given their respective prices and the available production technology. It is concerned with choosing between the different technically efficient combinations of inputs used to produce the maximum possible outputs or in reverse.

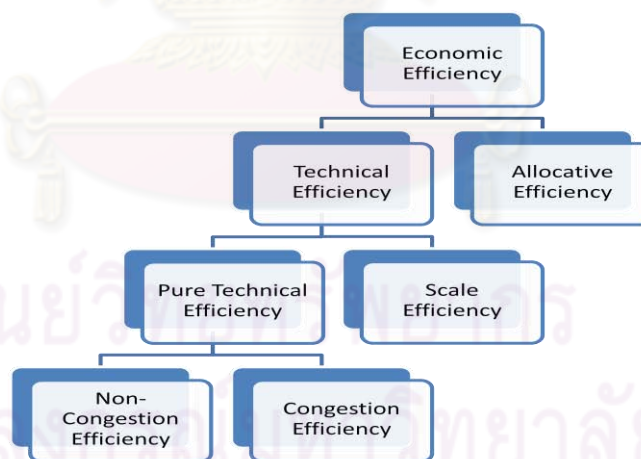


Figure 2.5 : Types of economic efficiency

Technical efficiency or technical efficiency under constant return to scale assumption (TECRS) can be decomposed into “pure” technical efficiency or technical efficiency under variable return to scale assumption (TEVRS) and scale efficiency (SE).

At the very first period of using the DEA measuring for technical efficiency score, there was an assumption of constant returns to scale, CRS. That's mean the firm was assumed that it operated at the most efficient economy of scale.

Pure technical efficiency was developed after that, in 1984, variable returns to scale, VRS, assumption was proposed by Banker et al. Because in the real world, there are some constraints those make the firm cannot operate at the optimal scale efficiency, SE. So, by this assumption SE of the firm is concerned.

Scale efficiency is the potential productivity gain from achieving optimal size of a firm. Scale efficiency pattern in economic is classified into 3 groups which are:

1. Increasing return to scale, IRS
2. Constant return to scale, CRS
3. Decreasing return to scale DRS

$P(X)$	=	Y	
$P(AX)$	=	BY	
A	$<$	B	for increasing return to scale, IRS
A	$=$	B	for constant return to scale, CRS
A	$>$	B	for decreasing return to scale, DRS

From above, $P(X)$ is represented for production function which has X as variable. By the function, X is used to produce Y . The next equation, X changes A time to AX which will make Y changed B time to BY . If the rate of changing of X , A , is lower than the rate of

changing of Y , B , economic calls increasing return to scale, IRS. While constant return to scale, CRS, is called if they are equal and decreasing return to scale, DRS, if A is more than B .

The IRS and DRS are concerned as scale inefficiency pattern while the optimal scale efficiency pattern is CRS. And at this CRS, the unit cost will be the lowest too.

2.2.1 Technique for efficiency evaluation

There are 4 main methods those are used for technical efficiency estimation. Which are:

1. Least-squares econometric production models, LS
2. Total factor productivity indices, TFP
3. Data envelopment analysis, DEA
4. Stochastic frontiers, SF

Each technique has its own strength and weakness as shown in Table 2.2. From many previous studies in healthcare efficiency, mainly DEA and SF were used and most were DEA.

	LS	TFP	DEA	SF
Parametric?	Y	N	N	Y
Account for noise?	Y	N	N	Y
Assume all firms are efficient?	Y	Y	N	N
Assumption	*	Cost min, Revenue max	N	*
Method used to measure				
- Technical change	Y	Y	Y	Y
- Technical efficiency	N	N	Y	Y
- Scale efficiency	Y	N	Y	Y
- Allocative efficiency	N	N	Y	Y
- Congestive efficiency	N	N	Y	N
Prices needed?	*	Y	*	*
Type of data				
- Cross-sectional	Y	Y	Y	Y
- Panel data	Y	Y	Y	Y
- Time-series	Y	Y		

Table 2.2: Summary of the properties of the 4 methods (Coelli, T., et al. 1998)

Y = yes, N = No, * = depend on the model used

2.2.2 Data envelopment analysis

Data envelopment analysis, or DEA, involves the use of linear programming methods to construct a non-parametric piecewise surface, or frontier, over the data, so as to be able to calculate efficiencies relative to this surface. By using the technique, relative technical efficiency scores of decision-making units is defined among the samples. DEA can handle measuring efficiency of multiple inputs and outputs model. Efficiency measurement concepts of DEA is to measure the distance between the current position of the firm and the most efficiency position, which is on the frontier, according to the assumption, input-orientated or output-orientated. The more the distance is, the lower efficiency the firm is.

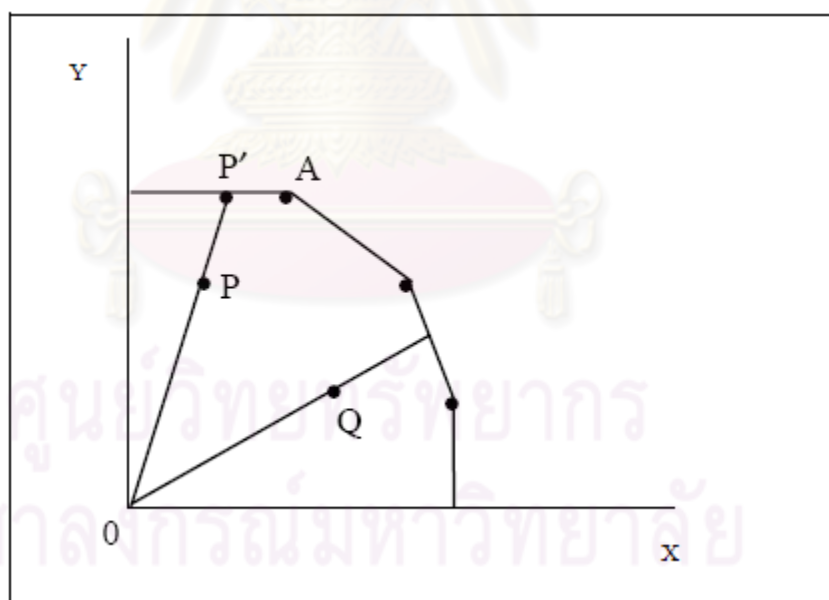


Figure 2.6: The efficiency frontier

From the figure 2.6 above, each point is a decision-making unit. While the piecewise line is a frontier which is lined between the most efficiency 4 points. P and Q are not on the

line because they're not efficiency. So, a straight line OP is drawn and went further to intercept with the frontier for calculation of the efficiency score at the point P. A ratio between distances PP' divided by distance OP' is a representative for an inefficiency of the firm P. For technical efficiency score, it can be calculate from distance OP divided by distance OP' or 1 minus inefficiency score.

Technical inefficiency score	=	
		$\frac{PP'}{OP'}$
Technical efficiency score	=	1 -
		$\frac{PP'}{OP'}$

2.2.3 Input and output – orientated DEA

Input-orientated measurement assumes that the firm is able to change quantities of inputs, while quantities of outputs are fixed, to meet up the most efficient point.

And in the reverse, output-orientated measurement assumes that quantities of outputs can be changed to match with the most efficiency point while quantities of inputs are fixed.

In healthcare researches, many studies used input-orientated assumption because:

1. Demand for healthcare is more inelastic than supply. The meaning is providers have more ability to change quantities of inputs to meet up the demand or output.
2. Implication from many studies aimed at cost minimization. So, measuring the technical efficiency score by the assumption can provide information for them to change quantities of inputs to meet up the same demand and gained higher efficient level.

2.2.4 DEA's assumption

At the very first period of using the DEA measuring for technical efficiency score, there was an assumption of constant returns to scale, CRS. That's mean the firm was assumed that it operated at the most efficient economy of scale.

$$P(X) = Y$$

$$P(AX) = BY$$

$A < B$ for increasing return to scale,
IRS

$A = B$ for constant return to scale,
CRS

$A > B$ for decreasing return to scale,
DRS

From above, $P(X)$ is represented for production function which has X as variable. By the function, X is used to produce Y . The next equation, X changes A time to AX which will make Y changed B time to BY . If the rate of changing of X , A , is lower than the rate of changing of Y , B , economic calls increasing return to scale, IRS. While constant return to scale, CRS, is called if they are equal and decreasing return to scale, DRS, if A is more than B .

After that, in 1984, variable returns to scale, VRS, assumption was proposed by Banker et al. Because in the real world, there are some constraints those make the firm cannot operate at the optimal scale efficiency, SE. So, by this assumption SE of the firm is concerned.

Standard input-orientated CRS and VRS assumptions were widely used in healthcare technical efficiency studies. But because of its weakness from non-parametric model, DEA cannot be checked for noise error by doing any statistical hypothesis testing. And also for only DEA using, further details in relation between each factors to the efficiency cannot be shown. Anyway, DEA is still popular for a quick used to determine any inefficiency inside the firm.

Another technique used together with DEA to provide deeper details of efficiency is by using econometric regression analysis, but not SF. This technique uses the technical efficiency score from DEA evaluation as a dependent variable and defines relevant independent variables to measure the relation to the score by looking at their coefficients. The independent variables can be inputs, outputs or any factors those researchers consider as the important variables to the score.

2.2.5 DEA model

CRS model – Assume there is data on K inputs and M outputs on each of N firms or DMU's. For the i -th DMU these are represented by the vectors x_i and y_i respectively. The $K \times N$ input matrix, X , and the $M \times N$ output matrix, Y , represent the data of all N DMU's. The purpose of DEA is to construct a non-parametric envelopment frontier over the data points such that all observed points lie on or below the production frontier. For the simple example of an industry where one output is produced using two inputs, it can be visualized as a number of intersecting planes forming a tight fitting cover over a scatter of points in three-dimensional space. The best way to introduce DEA is via the ratio form. For each DMU we would like to obtain a measure of the ratio of all outputs over all inputs, such as $u'y_i/v'x_i$ where u is an $M \times 1$ vector of output weights and v is a $K \times 1$ vector of input weights. To select optimal weights we specify the mathematical programming problem :

$$\begin{aligned} & \max_{u,v} (u'y_i/v'x_i), \\ \text{st} \quad & u'y_j/v'x_j \leq 1, \quad j=1,2,\dots,N, \\ & u, v \geq 0. \end{aligned}$$

This involves finding values for u and v , such that the efficiency measure of the i -th DMU is maximized, subject to the constraint that all efficiency measures must be less than or equal to one. One problem with this particular ratio formulation is that it has an infinite number of solutions. To avoid this one can impose the constraint $v'x_i = 1$, which provides:

$$\begin{aligned}
 & \max_{\mu, v} (\mu' y_i), \\
 & \text{st} \quad v' x_i = 1, \\
 & \quad \mu' y_j - v' x_j \leq 0, \quad j=1, 2, \dots, N, \\
 & \quad \mu, v \geq 0,
 \end{aligned}$$

Where the notation change from u and v to μ and \mathbf{v} reflects the transformation. This form is known as the multiplier form of the linear programming problem. Using the duality in linear programming, one can derive an equivalent envelopment form of this problem:

$$\begin{aligned}
 & \min_{\theta, \lambda} \theta, \\
 & \text{st} \quad -y_i + Y\lambda \geq 0, \\
 & \quad \theta x_i - X\lambda \geq 0, \\
 & \quad \lambda \geq 0,
 \end{aligned}$$

Where θ is a scalar and λ is a $N \times 1$ vector of constants. This envelopment form involves fewer constraints than the multiplier form ($K+M < N+1$), and hence is generally the preferred form to solve. The value of θ obtained will be the efficiency score for the i -th DMU. It will satisfy $\theta \leq 1$, with a value of 1 indicating a point on the frontier and hence a technically efficient DMU, according to the Farrell (1957) definition. Note that the linear programming problem must be solved N times, once for each DMU in the sample. A value of θ is then obtained for each DMU.

The piecewise linear form of the non-parametric frontier in DEA can cause a few difficulties in efficiency measurement. The problem arises because of the sections of the

piecewise linear frontier which run parallel to the axes which do not occur in most parametric functions. Some authors have suggested the solution of a second-stage linear programming problem to move to an efficient frontier point by maximizing the sum of slacks required to move from an inefficient frontier point to an efficient frontier point. This second stage linear programming problem may be defined by:

$$\begin{aligned} \min_{\lambda, OS, IS} & -(M1'OS + K1'IS), \\ \text{st} & -y_i + Y\lambda - OS = 0, \\ & \theta x_i - X\lambda - IS = 0, \\ & \lambda \geq 0, OS \geq 0, IS \geq 0, \end{aligned}$$

Where OS is an M^*1 vector of output slacks, IS is a K^*1 vector of input slacks, and $M1$ and $K1$ are M^*1 and K^*1 vectors of ones, respectively. Note that in this second-stage linear program, θ is not a variable, its value is taken from the first-stage results. Furthermore, note that this second-stage linear program must also be solved for each of the N DMU's involved.

There are two major problems associated with this second stage LP. The first and most obvious problem is that the sum of slacks is maximized rather than minimized. Hence it will identify not the nearest efficient point but the furthest efficient point. The second major problem associated with the above second-stage approach is that it is not invariant to units of measurement. The alteration of the units of measurement, say for a fertilizer input from kilograms to tones (while leaving other units of measurement unchanged), could result in

the identification of different efficient boundary points and hence different slack and lambda measures.

As a result of this problem, many studies simply solve the first-stage linear program for the values of the Farrell radial TE measures (θ) for each DMU and ignore the slacks completely, or they report both the radial Farrell TE score (θ) and the residual slacks, which may be calculated as

$$OS = -y_i + Y \lambda \quad \text{and}$$

$$IS = \theta x_i - X \lambda.$$

However, this approach is not without problems either because these residual slacks may not always provide all slacks or hence may not always identify the nearest efficient point for each DMU.

VRS model - the CRS assumption is only appropriate when all DMU's are operating at an optimal scale. Imperfect competition, constraints on finance, etc. may cause a DMU to be not operating at optimal scale. Banker, Charnes and Cooper(1984) suggested an extension of the CRS DEA model to account for VRS situations. The use of the CRS specification when not all DMU's are operating at the optimal scale will result in measures of TE which are confounded by SE. The use of the VRS specification will permit the calculation of TE devoid of these SE effects.

The CRS linear programming, LP, problem can be easily modified to account for VRS by adding the convexity constraint :

$$N1' \lambda = 1$$

To provide:

$$\begin{aligned} & \min_{\theta, \lambda} \theta, \\ \text{st} \quad & -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \\ & N1'\lambda = 1 \\ & \lambda \geq 0, \end{aligned}$$

Where $N1$ is and $N*1$ vector of ones. This approach forms a convex hull of intersecting planes which envelope the data points more tightly than the CRS conical hull and thus provides technical efficiency scores which are greater than or equal to those obtained using the CRS model. The VRS specification has been the most commonly used specification in the 1990's.

Calculation of SE – many studies have decomposed the TE scores obtained from a CRS DEA into two components, one due to SE and one due to pure TE. So,

$$TE_{I,CRS} = TE_{I,VRS} \times SE_I$$

Input orientations –

$$\begin{aligned}
 & \text{Min } \Phi \\
 & \sum_j \lambda_j x_{jm} \leq \Phi x_{j_0 m} \quad ; m = 1, 2, \dots, M \\
 & \sum_j \lambda_j y_{jn} \geq y_{j_0 n} \quad ; n = 1, 2, \dots, N \\
 & \lambda_j \geq 0 \quad ; j = 1, 2, \dots, J
 \end{aligned}$$

2.3 Regression analysis

Regression analysis or RA is based on econometrics model. Econometrics is the quantitative measurement and analysis of actual economic and business phenomena. It attempts to quantify economic reality and bridge the gap between the abstract world of economic theory and the real world of human activity. Econometrics allows us to examine data and to quantify the actions of firms, consumers, and governments. Econometrics has three major uses:

1. Describing economic reality
2. Testing hypotheses about economic theory
3. Forecasting future economic activity

The simplest use of econometrics is description. We can use econometrics to quantify economic activity because econometrics allows us to estimate numbers and put them in equations that previously contained only abstract symbols. This technique gives a much more specific and descriptive picture.

The second and perhaps most common use of econometrics is hypothesis testing, the evaluation of alternative theories with quantitative evidence. Much of economics involves building theoretical models and testing them against evidence, and hypothesis testing is vital to that scientific approach.

The third and most difficult use of econometrics is to forecast or predict what is likely to happen next in the future based on what has happened in the past. The accuracy of such forecasts depends in large measure on the degree to which the past is a good guide to the future. Business leaders and politicians tend to be especially interested in this use of econometrics because they need to make decisions about the future, and the penalty for being wrong is high. To the extent that econometrics can shed light on the impact of their policies, business and government leaders will be better equipped to make decisions.

Econometricians use regression analysis to make quantitative estimates of economic relationships that previously have been completely theoretical in nature.

Regression analysis is a statistical technique that attempts to explain movements in one variable, the dependent variable, as a function of movements in a set of other variables, called the independent or explanatory variables, through the quantification of a single equation.

The simplest single-equation linear regression model is:

$$y = c_0 + c_1 * x$$

The equation states that Y, the dependent variable, is a single-equation linear function of X, the independent variable. The model is a single-equation model because it's

the only equation specified. The model is linear because if you were to plot the equation it would be a straight line rather than a curve.

The C_s are the coefficients that determine the coordinates of the straight line at any point. C_0 is the constant of intercept term; it indicates the value of Y when X equals zero. C_1 is the slope coefficient, and it indicates the amount that Y will change when X increases by one unit.

Besides the variation in the dependent variable that is caused by the independent variable, there is almost always variation that comes from other sources as well. This additional variation comes in part from omitted explanatory variables. However, even if these extra variables are added to the equation, there still is going to be some variation in Y that simply cannot be explained by the model. This variation probably comes from sources such as omitted influences, measurement error, incorrect functional form, or purely random and totally unpredictable occurrences. By random we mean something that has its value determined entirely by chance.

Econometricians admit the existence of such inherent unexplained variation ("error") by explicitly including a stochastic (or random) error term in their regression models. A stochastic error term is a term that is added to a regression equation to introduce all of the variation in Y that cannot be explained by the included X s. It is, in effect, a symbol of the econometrician's ignorance or inability to model all the movements of the dependent variable.

The addition of a stochastic error term to the equation results in a typical regression equation:

$$y = c_0 + c_1 * x + e$$

Our regression notation needs to be extended to include reference to the number of observations and to allow the possibility of more than one independent variable. If we include a specific reference to the observations, the single-equation linear regression model may be written as:

$$y_i = c_0 + c_1 * x_i + e_i \quad (i = 1, 2, 3, \dots, n)$$

Where :

- y_i = the i-th observation of the dependent variable
- x_i = the i-th observation of the independent variable
- e_i = the i-th observation of the stochastic error term
- c_0, c_1 = the regression coefficients
- n = the number of observations

That is, the regression model is assumed to hold for each observation. The coefficients do not change from observation to observation, but the values of Y, X, and e do.

A second notational addition allows for more than one independent variable. Since more than one independent variable is likely to have an effect on the dependent variable, our notation should allow these additional explanatory Xs to be added. Then all variables can be expressed as determinants of Y in a multivariate linear regression model:

$$y_i = c_0 + c_1 * x_{1i} + c_2 * x_{2i} + c_3 * x_{3i} + \dots + e_i$$

Where : x_{1i} = the i-th observation of the first independent variable

x_{2i} = the i-th observation of the second independent variable

x_{3i} = the i-th observation of the third independent variable

And so on.

The meaning of the regression coefficient C_1 in this equation is the impact of a one unit increase in X_1 on the dependent variable Y , holding constant the other included independent variables. Similarly, C_2 gives the impact of a one-unit increase in X_2 on Y , holding the other X s constant. These multivariate regression coefficients serve to isolate the impact on Y of a change in one variable from the impact on Y of changes in the other variables.

Once a specific equation has been decided upon, it must be quantified. This quantified version of the theoretical regression equation is called the estimated regression equation and is obtained from a sample of data for actual X s and Y s.

$${}_eY_i = {}_eC_0 + {}_eC_1 * X_i$$

where: ${}_eY_i$ = estimated value of Y_i

${}_eC_0$ = estimated value of C_0

${}_eC_1$ = estimated value of C_1

The difference between the estimated value of the dependent variable (${}_eY_i$) and the actual value of the dependent variable (Y_i) is defined as the residual (r_i):

$$r_i = Y_i - {}_eY_i$$

The residual is the difference between the observed Y and the estimated regression line, while the error term is the difference between the observed Y and the true regression equation. Note that the error term is a theoretical concept that can never be observed, but the residual is a real-world value that is calculated for each observation every time a regression is run.

The most widely used method of obtaining these estimates is Ordinary Least Squares (OLS). OLS has become so standard that its estimates are presented as a point of reference even when results from other estimation techniques are used. OLS is a regression estimation technique that calculates the estimated coefficients, $\hat{\beta}$ so as to minimize the sum of the squared residuals, thus:

$$\text{OLS minimizes } \sum_{i=1}^n r_i^2 \text{ (i = 1, 2, 3, ..., n)}$$

Although OLS is the most-used regression estimation technique, it's not the only one. Indeed, econometricians have developed what seems like zillions of different estimation techniques. There are at least three important reasons for using OLS to estimate regression models:

1. OLS is relatively easy to use.
2. The goal of minimizing $\sum_{i=1}^n r_i^2$ is quite appropriate from a theoretical point of view.
3. OLS estimates have a number of useful characteristics.

The Classical Assumption must be met in order for OLS estimators to be the best available.

1. The regression model is linear, is correctly specified, and has an additive error term.
2. The error term has a zero population mean.
3. All explanatory variables are uncorrelated with the error term.
4. Observations of the error term are uncorrelated with each other (no serial correlation).
5. The error term has a constant variance (no heteroskedasticity).
6. No explanatory variable is a perfect linear function of any other explanatory variable(s) (no perfect multicollinearity).
7. The error term is normally distributed (this assumption is optional but usually is invoked).

Steps in applied RA:

1. Review the literature and develop the theoretical model.
2. Specify the model: Select the independent variables and the functional form.
3. Hypothesize the expected signs of the coefficients.
4. Collect the data. Inspect and clean the data.
5. Estimate and evaluate the equation.
6. Documents the results.

2.4 The previous studies

This chapter reviews previous studies from Charunwatthana (2007), Masiye (2007), Patmasiriwat (2006), Zere et al. (2006), Rebba and Rizzi (2006), Steinmann (2004), Linna et al. (2003), Riedel et al. (2002), Zavras et al. (2002), Mahannirankul (2000), Athanassopoulos et al. (1999), Linna (1998), Chang (1998), Gerrier and Valdmanis (1996), Grosskopf and Valdmanis (1993), Ozcan and Luke (1993), GAO (1990), Gianfrancesco (1990), Sexton et al. (1989), Sherman (1984), Banker et al. (1984), and Banker (1984).

Charunwatthana (2007) applied the data envelopment analysis to measure the hospital efficiency of public hospitals and identify the determinants of hospital efficiency and found that the numbers of bed, occupancy rate, geographic location and service complexity are associated with technical efficiency.

Masiye (2007) applied the data envelopment analysis to investigate health system performance to Zambian hospitals. The data was gathered from a sample of 30 hospitals throughout Zambia. The DEA model estimates an efficiency score for each hospital. A decomposition of technical efficiency into scale and congestion is also provided. It is found that overall Zambian hospitals are operating at 67% level of efficiency, implying that significant resources are being wasted. Only 40% of hospitals were efficient in relative terms. The study further reveals that the size of hospitals is a major source of inefficiency. Input congestion is also found to be a source of hospital inefficiency. Policy attention is drawn to unsuitable hospital scale of operation and low productivity of some inputs as factors that reinforce each other to make Zambian hospitals technically inefficient at producing and delivering services. It is argued that such evidence of substantial inefficiency would undermine Zambia's prospects of achieving its health goals.

Patmasiriwat (2006) studied on the relative efficiency of hospital cost in Thailand: The cases studies of 95 Central and General Hospital under the ministry of public health, based on data of the fiscal year 2005t. Two variables of interest here are: personnel costs and operating expenses. Hospital costs are assumed to vary with service provisions measured in 3 variables: inpatient day, outpatient service provided and the case of transferred patient (received). The result found that: the average efficiency was found to be 78%, based on the VRS (variable returns to scale assumption) of which 19 units lied on the cost- frontier. If the CRS (constant returns to scale) was adopted instead, then the average efficiency would be 71%. These results are understandable as the assumption of CRS is more rigid than the VRS assumption. The discusses was the hospital cost efficiency study should be continued for reasons that: not only that new knowledge of hospital management will be formally recorded and discovered that based on the Thai context, the findings from this type of study should be useful for policy-making in particular the present situation as our health budget is appropriated based on capitation and on prospective payment. An allocation for hospital units should be compatible to an efficient allocation rule rather than an 'average cost' allocation basis. There would be an inherent bias in favor of inefficient hospital units if the allocation be based on "average cost" and, in the long run, can lead to an undesirable risk of 'adverse selection'.

Zere et al.(2006) applied the data envelopment analysis to measure the technical efficiency of district hospitals in Namibia. All 30 public sector hospitals were included in the study. Hospital capacity utilization ratios and the data envelopment analysis (DEA) techniques were used to assess technical efficiency. The DEA model used three inputs and two outputs. Data for four financial years (1997/98 to 2000/2001) was used for the analysis.

To test for the robustness of the DEA technical efficiency scores the Jackknife analysis was used. The findings suggest the presence of substantial degree of pure technical and scale inefficiency. The average technical efficiency level during the given period was less than 75%. Less than half the hospitals included in the study were located on the technically efficient frontier. Increasing returns to scale is observed to be the predominant form of scale inefficiency. It is concluded that the existing level of pure technical and scale inefficiency of the district hospitals is considerably high and may negatively affect the government's initiatives to improve access to quality health care and scaling up of interventions that are necessary to achieve the health-related Millennium Development Goals. It is recommended that the inefficient hospitals learn from their efficient peers identified by the DEA model so as to improve the overall performance of the health system.

Rebba and Rizzi (2006) used the data envelopment analysis to measure hospital efficiency of a sample of Italian NHS hospitals. They showed how the choice of specific constraints on input and output weights (in accordance with health care policy makers' preferences) and the consideration of exogenous variables outside the control of hospital management (and linked to past policy-makers' decisions) can affect the measurement of hospital technical efficiency using the DEA. Considering these issues, the DEA method is applied to measure the efficiency of 85 (public and private) hospitals in Veneto, a Northern region of Italy. The empirical analysis allows them to verify the role of weight restrictions and of demand in measuring the efficiency of hospitals operating within a National Health Services (NHS). They found that the imposition of lower bound on the virtual weight of acute care discharges weighted by case-mix (in order to consider policy-maker objectives) reduces average hospital efficiency. Moreover, they showed that, in many cases, low

efficiency scores are attributable to external factors, which are not fully controlled by the hospital manager; especially for public hospitals low total efficiency scores can be mainly explained by past policy-makers' decisions on the size of the hospitals or their role within the regional health care service. Finally, non-profit private hospitals exhibit a higher total inefficiency while both non-profit and for-profit hospitals are characterized by higher levels of scale inefficiency than public ones.

Steinmann (2004) used the data envelopment analysis to measure and compare the inefficiency of German and Swiss hospitals. It seeks to answer the question of whether a given bundle of hospital services can be provided with fewer resources in the German federal state of Saxony compared to Switzerland, and whether findings are robust when attempts are made to take institutional differences into account. This study is of interest from three points of views. First, contrary to most existing work patient days are not treated as an output but as an input. Second, the usual DEA assumption of a homogeneous sample is tested and rejected for a large part of the observations. The proposed solution is to restrict DEA to comparable observations in the two countries. The finding continues to be that hospitals of Saxony have higher efficiency scores than their Swiss counterparts. The finding proves robust with regard to modifications of DEA that are motivated by differences in hospital planning in Germany and Switzerland. The conclusions are that in Germany, the hospital remuneration scheme makes patient days the primary target variable. Moreover, the fact that the observations are planned rather than actual quantities is of minor importance. In Switzerland, quality competition is enforced to some extent by patient migration, causing the number of cases to be emphasized as an objective. Both input and output quantities suggest that the hospitals of the German sample are roughly twice as

large as their Swiss counterparts. At the same time, they are far more homogeneous, which is remarkable in view of the many exclusion restrictions that had to be imposed on the Swiss sample. The larger size of German hospitals gives rise to the expectation that the DEA will indicate a larger share of units exhibiting constant and decreasing returns to scale in the German subsample. The German hospitals are more efficient on average than the Swiss. This finding is reinforced when taking into account that two-thirds of the Swiss observations cannot be projected on a German reference set, indicating that the two sets are largely disjoint. In the present DEA, calculated efficiency scores depend heavily on the standard homogeneity assumption. On the other hand, they may be considered largely robust against the choice of and changes in the exchange rate. Based on the fact that patient days relative to cases treated have been a more important performance indicator for German than for Swiss policy, counting patient days among the outputs in DEA should increase German efficiency scores more than the Swiss. This prediction is confirmed.

Linna et al. (2003) measured the productive efficiency of public dental health provision across Finland. The analysis was based on data envelopment analysis (DEA) using linear programming. In addition, they investigated various factors explaining the technical and cost efficiency of public dental care using a parametric Tobit model. These analyses revealed substantial variation in productive efficiency between health centres in different municipalities. The level of cost inefficiency was generally between 20% and 30%. Good dental health of the population, high rates of unemployment and high per capita expenditure on primary care in the municipality were associated with technical and cost inefficiency. According to the results, cost efficiency would not be improved by shifting input allocation towards more auxiliary manpower in health centres. Individual efficiency

scores were clearly sensitive to the choice of output specification. Changing the unit of output measurement from visit- to patient-based measures affected markedly the ranking of dental health centres. However, the set of exogenous correlates associated to inefficiency was strikingly similar for both types of output specification. More resources are needed if the coverage of public dental care is extended to all age groups. The health centre specific efficiency scores obtained in this study can be used locally to evaluate, design and implement structural changes in the production processes.

Riedel et al. (2002) investigated the evolution of efficiency and productivity in the hospital sector of an Austrian province for the time period 1994–1996. They used panel data to design non-parametric frontier models (Data Envelopment Analysis) and compared efficiency scores and time patterns of efficiency across medical fields. As health outcomes hardly can be measured in a direct way they make use of two different approaches for output measurement: In a first approach, they employ the number of case mix-adjusted discharges and of inpatient days, in a second they use credit points, which are calculated in course of the newly introduced diagnosis related group-type financing system. They calculate and compare individual efficiency scores for hospital wards as decision making units (DMU) in specified medical fields. To their knowledge the calculation of ward-specific efficiency scores has not up till now been the unit of non-parametric efficiency analysis. Their two models find different results: Model 1 with conservative output measurement calculates an average efficiency level of 96%, while model 2 with credit points for output measurement puts average efficiency at 70%. Whereas average efficiency in model 1 hardly changes and in model 2 increases modestly in the period 1994–1996, a closer look at single hospitals displays a variety of different efficiency developments over time.

Zavras et al. (2002) used DEA to evaluate efficiency and formulate policy within a Greek national primary health care network. This study provides evidence regarding the relative efficiency of primary health care centers, as well as implications for their ideal size. Utilizing DEA, a method of proper allocation of human resources by geographic district, municipality, or community was identified. Current health sector reform efforts should be planned on the basis of such findings. Furthermore, this model should be supplemented with valid demographic, socioeconomic, and epidemiological findings. Performing stratified DEA analyses (at each regional level) may become the basis for the creation of a national health care chart, matching available resources to the population and its health needs. DEA methods can help to pinpoint good and poor clinical and administrative practices and as such, to document the necessity for creation of new facilities, consolidation, or even abolishment of inefficient and costly centers. Thus, through providing on insight into the organization and the inefficiencies of the current system and by setting quantitative and qualitative benchmarks, this method could facilitate the effort towards meeting the goal of achieving equality and efficiency in health services.

Mahannirankul (2000) measured the efficiency of psychiatric hospitals under Mental Health Department by collecting information of budgeting of 13 Psychiatric Hospitals. The study focused on medical personnel's workload, use of patient's bed, necessity of patient's admission which are the limitation of Psychiatric care because in reality patient's admission often do without necessity, such as the homeless patients or patient without relatives (which cannot discharge) and this cause affected the use of patient's bed and medical personnel's workload automatically. The result found that the efficiency of the patient's bed use through the Pabon Lasso Scatter Plot Methodology: (1) The quadrant #1 (high bed occupancy rate

and low bed turnover rate) included 5 of 13. This implies that a hospital possibly had patient's bed over its demand or admission demand was low. (2) The quadrant #2 (low bed occupancy rate and high bed turnover rate) included 5 of 13. This implies that patient's bed supply were over admission demand and patient beds had been insignificantly used. (3) The quadrant #3 (high bed occupancy rate and high bed turnover rate) included 3 of 13. This implies that a hospital had efficiency utilized patient's bed due to its low loss utilization ratio. (4) The quadrant #4 (high bed occupancy rate and low bed turnover rate) none of all fell in this quadrant.

Athanassopoulos et al (1999) assessed the production and cost efficiency of 98 out of 126 hospitals of the Greek nation health system. The analysis is directly concerned with the degree of utilization of resources and the production efficiency of the general hospitals selected. For the measurement of the indices of efficiency, the internationally known method of Data Envelopment Analysis (modified to the particular characteristics of the Greek NHS) was used. The efficiency of Greek hospitals was assessed utilizing two alternative conceptual models: one focusing on production and the other on cost efficiency. The results, in both cases, indicated the scope for substantial efficiency improvements. The analysis has sought to discuss the policy implications resulting from the current efficiency status of the hospitals with reference to issues of resource re-allocation and optimal scale size.

Linna (1998) investigated the development of hospital cost efficiency and productivity in Finland in 1988–1994 using a comparative application of parametric and non-parametric panel models. Stochastic cost frontier models with a time-varying inefficiency component were used as parametric methods. As non-parametric methods

various DEA models were employed to calculate efficiency scores and the Malmquist productivity index. The results revealed a 3–5% annual average increase in productivity, half of which was due to improvement in cost efficiency and half due to technological change. The results by parametric and non-parametric methods compared well with respect to individual efficiency scores, time-varying efficiency and technological change. The state subsidy reform of 1993 did not seem to have any observable effects on the hospital efficiency.

Chang (1998) combined data envelopment analysis (DEA) with regression analysis to evaluate the efficiency of central government-owned hospitals over the five fiscal years between 1990 and 1994. Efficiency is first estimated using DEA with the choice of inputs and outputs being specific to hospital operations. A multiple regression model is then employed in which the efficiency score obtained from the DEA computations is used as the dependent variable. A number of hospital operating characteristics are chosen as the independent variables. The results indicate that the scope of services and proportions of retired veteran patients are negatively and significantly associated with efficiency, whereas occupancy is positively and significantly associated with efficiency. Furthermore, the results show that hospital efficiency has improved over time during the periods studied and, given the contemporary focus on concerns regarding efficiency in health care, the results provide an indication that inter-temporal efficiency gains are attainable in healthcare sector in anticipation of the implementation of National Health Insurance Programme (Act).

Gerrier and Valdmanis (1996) studied rural hospital performance and its correlates. The cost, technical, allocative and scale efficiencies of a sample of rural U.S. hospitals are calculated via linear programming models. Tobit analysis is used to assess possible

correlates of each of the efficiency measures. A large amount of dispersion in operating efficiency is found within our data set; the majority of the dispersion is due to technical inefficiency. The possible correlates affecting the hospital efficiency include quality of care, size, demand for services, the mix of services offered, the intensity of care provided and location and they found that allocative and scale are found to be negatively correlated with quality. The former finding is evidence that higher quality care requires an input mix that deviates from the efficient mix. Technical efficiency and size are found to have a U-shaped relationship - large and small hospitals are relatively more technically efficient than are medium-sized hospitals. The relationship between both allocative and scale efficiency and size follows an inverted-U pattern - being either too large or too small may be deleterious. The occupancy rate is a strong, positive correlate with cost, technical and scale efficiency. The relationship between occupancy and allocative efficiency is negative. The ratio of outpatients and the intensity of care provided (the number of intensive care unit days relative to all patient care days) both have positive effects on cost efficiency, while the ratio of outpatients is positively correlated with technical and scale efficiency as well. The positive relationship between the intensity of care provided and cost efficiency is unexpected. Note, however, that the result is significant at just the 10% level and that neither of the components of cost efficiency (technical and allocative efficiency) are significantly related to the intensity of care provided. The evidence of location differences in performance across the four states is found. In general, for-profit hospitals are found to outperform not-for-profit and public hospitals. Demand characteristics, quality of care, and the mix of services offered are also found to influence performance.

Grosskopf and Valdmanis (1993) applied the data envelopment analysis to evaluate hospital performance with case-mix-adjusted outputs. They compared hospital efficiency using a multiple input-output approach in two ways: one way used a straightforward count of inpatient days and outpatient services as outputs; and the second used a case mix-adjusted count of inpatient services and outpatient care as outputs. Their results show that there was no difference when they incorporated the case-mix index, either as a weighting device or as a separate output.

Ozcan and Luke (1993) conducted a national study of the efficiency of hospitals in urban markets. Using a sample of 3,000 urban hospitals, this article examines the contributions of selected hospital characteristics to variations in hospital technical efficiencies, while it accounts for multiple products and inputs, and controls for local environmental variations. Four hospital characteristics are examined: hospital size, membership in a multi-hospital system, ownership, and payer mix (managed care contracts, percent Medicare, and percent Medicaid). Ownership and percent Medicare are consistently found to be related significantly to hospital efficiency. Within the ownership variable, government hospitals tend to be more efficient and for-profit hospitals less efficient than other hospitals. Higher percentages of Medicare payment are negatively related to efficiency. While not consistently significant across all five of the MSA size categories in which the analyses are conducted, possession of managed care contracts, membership in a multi-hospital system and size all are consistently related positively to hospital technical efficiency. These variables are also all significant when the hospitals are examined in a combined analysis. Percent Medicaid was not significant in any of the analyses.

A recent General Accounting Office study [GAO (1990)] finds that hospital size, occupancy rate, ownership, and regional location are all related to financial distress and closure among hospitals.

Gianfrancesco (1990) cites the number of beds, occupancy, geographic location, and ownership as factors likely to affect efficiency.

Sexton et al (1989) applied the methodology of data envelopment analysis (DEA) to the set of Veterans Administration medical centers (VAMC) to evaluate their relative managerial efficiencies. Each VAMC was viewed as a producer of multiple outputs and a consumer of multiple inputs. DEA uses linear programming to identify resources that were underutilized and services that were inefficiently produced. Managerial strategies based on the dual variables were constructed to indicate the manner in which inefficient VAMCs may be made efficient. The analysis showed that relative inefficiency existed in about one third of the VAMCs nationwide. Elimination of this inefficiency would save the VA over \$300 million annually on personnel, equipment, drugs, and supplies, without reducing the level of services provided. A subsequent analysis of co-variance revealed that VAMCs affiliated with a university were generally less efficient than those without such an affiliation. A similar finding was obtained for larger VAMCs relative to smaller medical centers. In neither case, however, should these results be construed to imply that VAMCs should terminate their university affiliations or that VAMCs should be made smaller since factors other than relative efficiency are clearly as or more important in such decisions.

Sherman (1984) suggested a new technique for identifying inefficient hospitals, Data Envelopment Analysis (DEA), is field tested by application to a group of teaching hospitals.

DEA is found to provide meaningful insights into the location and nature of hospital inefficiencies as judged by the opinion of a panel of hospital experts. DEA provides insights about hospital efficiency not available from the widely used efficiency evaluation techniques of ratio analysis and econometric regression analysis. DEA is, therefore, suggested as a means to help identify and measure hospital inefficiency as a basis for directing management efforts toward increasing efficiency and reducing health care costs.

Banker et al. (1984) showed some models for estimating technical and scale inefficiencies in data envelopment analysis. In management contexts, mathematical programming is usually used to evaluate a collection of possible alternative courses of action en route to selecting one which is best. In this capacity, mathematical programming serves as a planning aid to management. Data Envelopment Analysis reverses this role and employs mathematical programming to obtain ex post facto evaluations of the relative efficiency of management accomplishments; however they may have been planned or executed. Mathematical programming is thereby extended for use as a tool for control and evaluation of past accomplishments as well as a tool to aid in planning future activities. The CCR ratio form introduced by Charnes, Cooper and Rhodes, as part of their Data Envelopment Analysis approach, comprehends both technical and scale inefficiencies via the optimal value of the ratio form, as obtained directly from the data without requiring a priori specification of weights and/or explicit delineation of assumed functional forms of relations between inputs and outputs. A separation into technical and scale efficiencies is accomplished by the methods developed in this paper without altering the latter conditions for use of DEA directly on observational data. Technical inefficiencies are identified with failures to achieve best possible output levels and/or usage of excessive amounts of inputs.

Methods for identifying and correcting the magnitudes of these inefficiencies, as supplied in prior work, are illustrated. In the present paper, a new separate variable is introduced which makes it possible to determine whether operations were conducted in regions of increasing, constant or decreasing returns to scale (in multiple input and multiple output situations). The results are discussed and related not only to classical (single output) economics but also to more modern versions of economics which are identified with "contestable market theories."

Banker (1984) estimated most productive scale size using data envelopment analysis. The relation between the most productive scale size (mpss) for particular input and output mixes and returns to scale for multiple-inputs multiple-outputs situations is explicitly developed. This relation is then employed to extend the applications of Data Envelopment Analysis (DEA) introduced by Charnes, Cooper and Rhodes (CCR) to the estimation of most productive scale sizes for convex production possibility sets. It is then shown that in addition to productive inefficiencies at the actual scale size, the CCR efficiency measure also reflects any inefficiencies due to divergence from the most productive scale size. Two illustrations of the practical applications of these results to the estimation of most productive scale sizes and returns to scale for hospitals and stem-electric generation plants are also provided to emphasize the advantage of this method in examining specific segments of the efficient production surface.

CHAPTER III

RESEARCH METHODOLOGY

This chapter explains methodology in this study. The following in this chapter is divided into, section 3.1 summarizes type of collected data. Section 3.2 tells about method to measure hospital efficiency by DEA model and its specification. Section 3.3 explains about method to measure effect of determinants to hospital efficiency by regression analysis and its specification.

3.1. Type of collected data

This study used sixty-four secondary decision making units (n=64) from sixteen psychiatric hospitals under the Department of Mental Health in Thailand since fiscal year 2007 – 2010. They were collected from the department and were treated as panel data.

The analysis consists of 2 stages. The first stage will be that all of hospital efficiency scores computed using data envelopment analysis programme, version 2.1 (DEAP 2.1) designed by Coelli. In the second stage of analysis, method to measure effect of determinants to hospital efficiency is regression analysis and its specification. These analyses of regression model were performed with Eviews version 6

Output and Input variables

DEA model is based on inputs and outputs as follows:

Input variables:

Two Input variables were selected as a representative for capital input.

1. Total number of hospital staff (STAFF)
2. Total number of beds (BED)

Output variables:

Three dimensions of hospital activity's output variables were used as follows:

1. Out-patient service was observed the activity by number of out-patient visits (OPD),
2. In-patient service was observed the activity by number of in-patient bed-days (IPD),
3. Educational service was observed the activity by number of psychiatric nurse trainees (TRAIN). There are nine hospitals which do not provide the training in the period.

For the regression analysis model, seven independent variables representing the factors likely to impact on efficiency performance of sixteen psychiatric hospitals are as follows:

- 1) The OPD/STAFF ratio

- 2) The STAFF/BED ratio
- 3) The IPD/BED ratio
- 4) Average length of stay(ALOS)
- 5) Hospital accreditation level (HA).
- 6) Geographic - Due to the hospitals are located in all parts of Thailand, so classification by region (Region) of hospital location was selected.
- 7) The educational services by using dummy variable

3.2. DEA specification

Output-orientated DEA model was used to measure technical efficiency of decision making units. Computer program named DEAP version 2.1 by Coelli handled the analysis. STAFF and BED were used as input variables, and OPD, IPD, and TRAIN were used as output variables. Efficiency measurement was done by pooling sixty-four decision making units as panel data in the same measurement by using STAFF, BED, OPD, IPD, and TRAIN in the model.

The DEA model

$$\max_{u,v} (u'y_i/v'x_i),$$

$$\text{st} \quad u'y_j/v'x_j \leq 1, \quad j=1,2,\dots,N,$$

$$u, v \geq 0.$$

Where u is an $M \times 1$ vector of output weights

v is a $K \times 1$ vector of input weights.

y is output variable

x is input variable

3.3. Regression analysis specification

Regression analysis was used to estimate coefficients of determinants regressed on technical efficiency score under variable returns to scale model (TEVRS). Eviews version 6 handled this part. All sixty-four decision making units are used in:

The regression analysis model:

$$TEVRS_i = a_0 + a_1 OPDSTAFF_i + a_2 STAFFBED_i + a_3 IPDBED_i + a_4 ALOS_i + a_5 DUMHA_i + a_6 DUMREG_i + a_7 DUMTRAIN_i + e_i \quad (1)$$

Where

$TEVRS_i$ = technical efficiency score under variable returns to scale model of i -th observation,

i = observation,

a_0 = constant,

a_1 = coefficient of *OPDSTAFF*

a_2 = coefficient of *STAFFBED*

a_3 = coefficient of *IPDBED*

a_4	= coefficient of <i>ALOS</i>
a_5	= coefficient of <i>DUMHA</i>
a_6	= coefficient of <i>DUMREG</i>
a_7	= coefficient of <i>DUMTRAIN</i>
e_i	= disturbance of i-th observation,

Table 3.1 Independence Variables for the regression analysis model

Variables	Definition	Unit of measurement
$OPDSTAFF_i$	Number of out-patient visits / Number of staff of i-th observation	Visits/person
$STAFFBED_i$	Number of staff / Number of bed of i-th observation	Person/bed
$IPDBED_i$	Number of in-patient case/number of bed of i-th observation	Case/bed
$ALOS_i$	average length of stay of i-th observation	Day/case
$DUMREG_i$	dummy variable of region	1= central
$DUMHA_i$	dummy variable of hospital accreditation level	1 = level 3
$DUMTRAIN_i$	dummy variable of training hospital	1 = training hospital

Hypothesis:

1) The OPD/STAFF ratio is positively associated with technical efficiency. Because increasing OPD/STAFF means utilizing more labor capacity producing OPD then it increases efficiency.

2) The STAFF/BED ratio is positively associated with technical efficiency. The STAFF/BED ratio represents the combination of capital and labor input or hospital scale. Increasing STAFF/BED means more input capacity to produce then it increases efficiency.

3) The IPD/BED has a positive impact on technical efficiency. Because increasing IPD means utilizing more capital capacity producing IPD then it increases efficiency.

4) The average length of stay (ALOS) was negatively related to technical efficiency. An important measurement of the operational index is ALOS (Brownell and Roos, 1995 in Chang, 2010). A shorter ALOS represents better treatment and means being able to treat more patients (Clarke, 2002 in Chang, 2010).

5) Quality of services (the level of HA) is negatively associated with efficiency. Because acquiring hospital accreditation means consuming inputs for other dimensions besides producing OPD and IPD. Due to we do not handle all dimensions in this analysis, then accredited hospital should show less efficiency level than non accredited hospital.

6) Geographic data (regional) is positively associated with technical efficiency. More skillful staff and technologies work in central region of the country. Because we do not separate inputs by skill level, so the central region hospital should show higher efficiency than the others.

7) Ability to train the psychiatric nurse trainees is positively associated with technical efficiency. Because being training hospital means utilizing more input capacity producing psychiatric nurse trainees then it increases efficiency.

CHAPTER IV

RESULTS AND DISCUSSION

This chapter analyzes secondary data of 64 decision making units from fiscal year 2007 to 2010 in sixteen psychiatric hospitals under the Department of Mental Health in Thailand. The following is divided into 4 sections: Section 4.1 showed the descriptive statistics analysis, Section 4.2 informed efficiency result from technical efficiency analysis using DEA model. Section 4.3 told about regression analysis. Section 4.4 described the findings discussion.

4.1. Descriptive statistics analysis

Data was complete in the required variables for 12 psychiatric hospitals and 4 mental health institutes. This section descriptive was shown overall picture of average inputs utilized and outputs produced. For convenience, the researcher will use alphabetic code to represent each hospital and the data which showed on the table is simplified by re-scaling and rolled up to two decimal.

Average of data from 2007 to 2010 in each hospital is summarized in Table 4.1 The data showed average numbers of two representatives of input factor. Number of all staff represented the labor input, and number of all bed, represented the capital input. On average number of staff, there are 221 persons (minimum is 47 persons in F hospital and maximum is 486 persons in A hospital) with standard deviation 138 persons. And there are 544 beds (minimum is 60 beds in N hospital and maximum is 2,280 beds in D hospital) with standard deviation 575 beds.

Table 4.1 Descriptive statistic of output and input variables

Hospital	Mean (year 2007-2010)					
	STAFF (100 persons)	BED (100 beds)	OPD (100,000 visits)	IPD (10,000 bed day)	TRAIN (person)	LOS (day/IPD case)
A	4.86	8.92	0.22	45.37	32.00	49.48
B	1.28	3.30	0.07	11.14	23.50	38.36
C	2.93	6.10	0.06	15.04	35.25	26.51
D	4.22	22.80	1.23	134.26	51.75	82.40
E	1.23	1.50	0.10	3.56	0.00	14.83
F	0.47	1.20	0.04	3.08	0.00	20.51
G	2.17	3.00	0.18	13.82	0.00	30.07
H	2.76	3.72	0.16	13.93	0.00	30.07
I	0.58	1.20	0.05	3.32	0.00	21.61
J	3.83	7.50	0.12	37.00	37.75	50.74
K	0.71	1.20	0.06	4.31	0.00	19.68
L	1.05	3.00	0.10	3.16	0.00	20.70
M	2.42	7.00	0.12	39.99	39.00	30.46
N	0.94	0.60	0.06	4.43	0.00	13.39
O	3.34	13.00	0.13	45.29	45.00	58.28
P	2.63	3.00	0.14	10.02	0.00	27.71
Mean	2.21	5.44	0.63	24.23	16.52	33.42
SD	1.38	5.75	0.33	33.29	20.17	18.47
Min	0.47	0.60	0.04	3.08	0.00	13.39
Max	4.86	22.80	1.23	134.26	51.75	82.40

Next, number of out-patient visits, number of in-patient bed days, and number of psychiatric nurse trainees are representatives for outputs of each hospital. On average each hospital has 63,000 out-patient visits (minimum is 4,000 visits in hospital F and maximum is 123,000 visits in hospital D) with 33,000 visits as standard deviation. For in-patient bed days, average service is 242,300 bed days (minimum is 30,800 bed days in hospital F and maximum is 1,342,600 bed days in hospital D) with 332,900 bed days as standard deviation. For psychiatric nurse training, there are seven hospitals those trains psychiatric nurse trainees which are hospital A, B, C, D, J, M, and O. Anyway, the table shows overall average from sixteen hospitals. Average trained psychiatric nurse trainees are about 17 persons (maximum is about 52 persons from hospital D). Last, average length of stay is about 33 days/case (minimum is about 13 days/ case in hospital N and maximum is about 82 days/ case in hospital D).

While classified all hospitals using the number of bed by criteria of the Bureau of policy and strategy, Ministry of Public Health hospitals can be divided into four categories reflecting the size of the hospital as showed in table 4.2 below The findings shows that a majority of the sample is extra large size hospitals (37.5%) and the minority is small size hospital (6.65%).

Table 4.2 Descriptive statistic of hospital size

Hospital size	Hospital	no
Extra Large (more than 500 beds)	A C D J M O	6(37.5%)
Large (200-500 beds)	B G H L P	5(31.25%)
Medium (90-150 beds)	E F I K	4 (25%)
Small (60 beds)	N	1(6.65%)

STAFF/BED ratio represented input combination between labor and capital input. Using the ratio interval, the hospitals were divided into six groups as shown in Table 4.3 and the Figure 4.1. The N hospital has a large number of personnel compared to the total number of beds. Meanwhile, the hospital D has a large number of beds compared to the total number of personnel.

Table 4.3 STAFF/BED ratio by interval

STAFF/BED ratio	Hospital	n
More than 1	N	1
0.80-1.00	P E	2
0.60-0.79	G H	2
0.40-0.59	A C I J K	5
0.0-0.39	B F L M O D	6

The Figure 4.1 shows STAFF/BED ratio of each hospital on the Y-axis, and year on the X-axis to reflect changing trends in input. It can be concluded that during the year 2007-2010 inputs were changed slightly. Trend of inputs changing found the I hospital is likely to decrease slightly



4.2 Efficiency result from Technical efficiency analysis using DEA model

4.2.1 Overall technical efficiency analysis

Technical efficiency analysis is done by using DEAP version 2.1 in this section. The analysis was shown the pool all sixty-four decision making units as panel data and were analyzed in the output orientated DEA model at the same time (n=64). The variable return to scale (VRS) DEA model estimated for the year 2007-2010 indicates average technical efficiency score of 84%. The average scale efficiency score was 85%. Summary of technical efficiency score by hospital size was shown in Table 4.4.

Table 4.4 The overall TE results summary by hospital size

Hospital size	No	Mean Scores	
		TEVRS	SE
Extra Large(more than 500 beds)	6	0.96	0.92
Large (200-500 beds)	5	0.86	0.75
Medium (90-150 beds)	4	0.62	0.92
Small (60 beds)	1	0.77	0.98
Total	16	0.84	0.85

The extra large hospital group (more than 500 beds) was higher pure technical efficiency score, while pure technical inefficiency was more prevalent in medium (90-150 beds) and small (60 beds) hospital. The small hospital (60 beds) was higher scale efficiency scores and the scale inefficiency was more in large hospitals (200-500 beds).

4.2.2 Pure technical efficiency analysis

There are only 2(12.5% A, D hospital) out of 16 psychiatric hospitals are technically efficient hospitals that were located on the frontier (TE score=100%). About 56.25 % of all inefficient hospitals have efficiency scores more than 80% and 2(12.5% F, I hospital) out of those has scores less than 60% in table 4.5.

Table 4.5 The average TEVRS scores by interval

TEVRS Scores	No	Percent
100%	2	12.5
80-99%	9	56.25
60-79%	3	18.75
Less than 60%	2	12.5
Total	16	100

The result further classified the hospitals into 2 groups by using the educational services of training the psychiatric nurse. The overall TEVRS of no training group were shown in table 4.6 below. The result found that all of no training group of hospitals were pure technical inefficiency .The hospitals G and N were higher TEVRS Scores (99%) of all, while the hospital F was the lowest (46%). The L hospital changes were likely to decrease each year, while F hospital changes were likely to increase.

Table 4.6 The overall TEVRS Scores of each hospital of no training group

Hospital	TEVRS				Mean
	2007	2008	2009	2010	
E	1.00	0.81	0.83	0.83	0.87
F	0.48	0.42	0.44	0.51	0.46
G	1.00	0.97	1.00	1.00	0.99
H	0.89	0.83	0.80	0.81	0.83
I	0.44	0.54	0.53	0.51	0.51
K	0.66	0.68	0.59	0.61	0.64
L	1.00	0.76	0.70	0.67	0.78
N	1.00	1.00	0.92	1.00	0.98
P	0.77	0.78	0.76	0.76	0.77

For the training group of hospitals there are 2 (A, D hospital) of all are technically efficient hospitals that were located on the frontier (TEVRS score=100%) and all of inefficient hospitals have efficiency scores more than 80%. The M hospital changes were likely to decrease each year, while B hospital changes were likely to increase. It also revealed that the no training group was more inefficient than the training group.

ศูนย์วิจัยทั่วไป
จุฬาลงกรณ์มหาวิทยาลัย

Table 4.7 The overall TEVRS Scores of each hospital of training group

Hospital	TEVRS				Mean
	2007	2008	2009	2010	
A	1.00	1.00	1.00	1.00	1.00
B	0.88	0.88	0.98	1.00	0.93
C	0.88	0.91	0.95	0.93	0.92
D	0.99	1.00	1.00	1.00	1.00
J	1.00	0.87	0.98	1.00	0.96
M	1.00	1.00	0.94	0.93	0.97
O	0.91	0.93	0.85	0.88	0.89

ศูนย์วิทยทรัพยากร
จุฬาลงกรณ์มหาวิทยาลัย

4.2.3 Scale efficiency analysis

The table 4.8 showed scale efficiency Scores by hospital size and found that the average scale efficiency score of all psychiatric hospitals is 85%. The large hospitals group (200-500 beds) is less scale efficient score than any group with the lowest minimum scale efficient score.

Table 4.8 The scale efficiency Scores by hospital size

Hospital size	No	scale efficiency score		
		Mean	Min	Max
Extra Large(more than 500 beds)	6	0.92	0.64	1.00
Large (200-500 beds)	5	0.75	0.46	1.00
Medium (90-150 beds)	4	0.92	0.78	1.00
Small (60 beds)	1	0.98	0.95	1.00
Total	16	0.85	0.84	0.85

The results of table 4.9 below showed that mostly 13(81.25%) of all hospitals had scale inefficiency. Only 3(18.75% C, M, B hospital) out of all hospitals had scale efficiency. All of the medium and small hospital had scale inefficiency.

Table 4.9 The scale efficiency Status by hospital size

Hospital size	scale efficiency score		Total
	efficient	inefficient	
Extra Large(more than 500 beds)	2(33.33%)	4(66.67%)	6
Large (200-500 beds)	1(25%)	4(75%)	5
Medium (90-150 beds)	-	4(100%)	4
Small (60 beds)	-	1(100%)	1
Total	3(18.75%)	13(81.25%)	16

The scale efficiency results further revealed the pattern of scale inefficiency of each hospital classified by training activity in table 4.10 and 4.11. It also found that mostly of inefficient pattern of both no training and training group were decreasing return to scale (DRS). Only 3 (8.33%) of 36 DMUs (Decision making units) were increasing return to scale in no training group. The N hospital trended to be increasing return to scale (IRS).

Table 4.10 Scale efficiency (SE) Scores of no training group hospital

Hospital	Scale efficiency (SE) Scores			
	2007	2008	2009	2010
E	1	0.784*	0.784*	0.783*
F	0.984**	0.976*	0.921*	0.926*
G	0.788*	0.76*	0.73*	0.663*
H	0.637*	0.608*	0.899*	0.765*
I	0.869*	0.978*	0.965*	0.975*
K	0.904*	0.873*	0.981*	1
L	1	0.46*	0.467*	0.462*
N	0.996**	1	0.955**	1
P	0.734*	0.686*	0.694*	0.615*

** = IRS(increasing return to scale) * = DRS (decreasing return to scale)

The same as no training group results. The majority of inefficient pattern of training group were decreasing return to scale. There are 2 (7.14% B and C hospital) of 28 DMUs were increasing return to scale.

Table 4.11 Scale efficiency (SE) Scores of training group hospital

Hospital	Scale efficiency (SE) Scores			
	2007	2008	2009	2010
A	0.796*	0.883*	0.805*	0.774*
B	0.981*	0.992*	0.999**	1
C	0.946*	0.998**	0.809*	0.809*
D	0.991*	0.943*	1	0.811*
J	1	0.883*	0.86*	0.768*
M	1	1	0.98*	0.992*
O	0.904*	0.783*	0.755*	0.743*

** = IRS (increasing return to scale) * = DRS (decreasing return to scale)

According to the results we suggest that downscaling in the hospitals with decreasing return to scale and shift resources to those with increasing return to scale (such as N hospital). Because there are few of hospitals with increasing return to scale on this findings, so we recommend balancing the STAFF/BED ratio appropriately if possible.

4.3. Regression analysis

It is important to identify factor determining efficiency of hospital this section will be the result of regression. To see how large and significance explanatory variables affect overall technical efficiency level, we do regression analysis on TEVRS. This part presents a result from regression analysis of the model below, and table 4.8 shows the result.

$$TEVRS_i = a_0 + a_1OPDSTAFF_i + a_2STAFFBED_i + a_3IPDBED_i + a_4ALOS_i + a_5DUMHA_i + a_6DUMREG_i + a_7DUMTRAIN_i + e_i$$

Table 4.8 The result of regression analysis

Variables	Coeff.	SE	t-stat	p-value
Constant	0.337	0.047	7.041	0.000
OPDSTAFF	0.989	0.095	10.453	0.000
STAFFBED	0.058	0.049	1.155	0.252
IPDBED	0.449	0.132	3.398	0.001
ALOS	0.153	0.052	2.947	0.004
DUMHA	-0.013	0.018	-0.716	0.476
DUMREG	-0.012	0.017	-0.718	0.475
DUMTRAIN	0.339	0.033	10.117	0.000
n		64		
R square		0.794		
Adjusted R square		0.768		
Log likelihood		95.902		

The regression analysis results showed coefficients of STAFFBED, dummy of hospital accreditation, and dummy of regions are not significantly different at level of 0.05.

The OPDSTAFF, IPDBED and dummy of training activity variables are significant at the level of 0.001. The average length of stay is significant at the level of 0.01. All significant coefficients show the same relationship as expected. The result can be explained as following:

OPDSTAFF has a positive relationship with technical efficiency as increasing in outpatient visit or decreasing staff consumption which means increasing output and decreasing input those can be yield to increasing in technical efficiency. Changing in input should be concern about pattern of scale inefficiency of each hospital.

IPDBED has a positive relationship with technical efficiency as expected. This finding corresponds to the study of Charunwatthana (2007) that the numbers of bed was positively associated with technical efficiency. This implies the same as OPDSTAFF because IPDBED is such a output/input ratio. Increasing the number of inpatient case might not be practical implementing. So bed re-allocation is recommended, but changing of number of bed depends on the pattern of scale inefficiency.

ALOS has a positive relationship with technical efficiency different from expected. The reason to explain this finding is that increasing ALOS causes higher efficiency since more labor and capital capacities are utilized. In other words, while LOS increases, bed days which are main output also increase. But in the treatment dimension, the shorter LOS represented the better treatment. Therefore, this variable is correlated with the positive and negative impact on technical efficiency.

We used training activity as a dummy variable with positively relationship hypothesis. The results reveal the positive relationship between training activity and

technical efficiency. Being training hospital has higher real technical efficiency for about 0.3 units than not being one.

4.4. Discussion

The results are discussed for the implications in this section. Section 4.4.1 provides suggestion to overall adjustment for a better efficiency level, and section 4.4.2. Provides the policy direction is suggested

4.4.1. Adjustment for better efficiency level

Input savings

About 16% inefficiency levels are observed. This implied that if we can manage the inefficient hospitals to be as good as their best peers, we can save loss up to 16% of resources used in running the hospitals. The input savings are aggregates for the whole system.

Adjustment for better efficiency level

In DEA analysis, we have done pooling analysis (n=64).It shows most decision making units have variable return to scale technical efficiency scores (TEVRS) between 0.46 - 1.00. There are only 2 hospitals located on the frontier (TE score=100%). The average pure technical efficiency score is 84% and average scale efficiency scores is 85%. In overall picture, the extra large hospital group (more than 500 beds) is higher pure technical efficiency score, while pure technical inefficiency is more prevalent in medium (90-150

beds) and small (60 beds) hospital. The small hospital (60 beds) was higher scale efficiency scores and the scale inefficiency was more in large hospitals (200-500 beds). By classified hospitals into 2 groups using the training activity, the findings showed that no training group is higher level in both pure technical inefficiency and scale inefficiency scores. Mostly of the scale inefficiency pattern is decreasing return to scale.

Due to the variables used in this study, the interpretation of efficiency means how the decision making unit shows good utilization of inputs (which are STAFF and BED) to produce outputs (which are OPD, IPD, and TRAIN.) However other relationships outside the model cannot be explained by this study, such as management system, quality of health care, research and development, etc. The results from the regression analysis are informative enough to inform policy makers about how to adjust their decision making units to get better efficiency level. We would like to make some suggestions as a solution for real technical efficiency loss, and scale inefficiency.

First suggestion is about pure technical efficiency, which presents working capacity of inputs, can be increased by motivation full capacity utilization of inputs. Together with result from the regression analysis, the solution is to increase either OPDSTAFF or IPDBED variables which means utilizing more staff and bed. Increasing in targeting output production or reducing input units are both possible policies. Also, ALOS and DUMTRAIN show positive relationship to TEVRS, so increasing ALOS or having psychiatric nurse training activity can increase the real technical efficiency by making the hospital utilizes more on its inputs.

Second, as decreasing returns to scale is the main cause of scale inefficiency, downscaling hospital size is required to solve such the problem. Input reduction is suggested in order to solve the problem together with increasing real technical efficiency issue. For some decision making units which are operating at increasing returns to scale, increasing in targeting output production is suggested. In conclusion, we suggest to downscaling in the hospitals with decreasing return to scale and shift resources to those with increasing return to scale (N hospital especially bed capacity). Because there are a few hospitals with increasing return to scale on the findings, so appropriate balancing the STAFF/BED ratio should be considered at the same time. Re-allocate the number of bed may be practically done than the personnel re-allocation

4.4.4. Policy direction

From the overall findings and implications, we would like to suggest three key policy directions. First of all, each hospital should keep track on its own efficiency level and learn from the best peer to improve individual efficiency level by using knowledge management system and etc.

Second, suggestion was about inputs and outputs management. About the input, the most of all scale inefficiency of this study are in DRS pattern .Downscaling of the DRS-hospital by re-allocation of inputs which are staff and bed is recommended However the Department of Mental Health has already implement some re-allocation policies . Then findings of this study are such the evidence base to support those policy directions. About outputs, according to the regression results, promotion and support the development of

proactive outpatient services in order to increase OPD visit is recommended. Third, we should focus more on capacity building of nurse training program in more hospital.



ศูนย์วิทยุทรัพยากร
จุฬาลงกรณ์มหาวิทยาลัย

CHAPTER V

CONCLUSION AND RECOMMENDATION

This chapter concludes our results to answer research questions and objectives in section 5.1. Section 5.2 talks about the limitations of this study. Section 5.3 tells suggestion for further study respectively.

5.1. Conclusion

During the past decade health care systems have been under increasing pressure to improve performance to guarantee high quality services and better access to health care. Improving Health care performance is important because they can boost the well being as well as standard lining and the economic growth. The quest for high performance in health care has been difficult and intractable problem. Due to limited resources, the solution to solve this problem is how to use resources at the most efficient way. To know how good each hospital is operated, efficiency measurement is in charge of this. So, we did this study to answer the following questions,

1) What level are technical efficiency scores of psychiatric hospitals under the Ministry of Public Health?

2) What are the factors determining their efficiency?

So, to answer the questions, we ran a study to meet our objectives as,

1. To measure the hospital efficiency of psychiatric hospitals under the Department of Mental Health in Thailand in terms of technical efficiency.

2. To identify the factors determining the efficiency of hospitals.

We adopted a technique called data envelopment analysis, or DEA, to measure the hospital efficiency together with regression analysis to measure effects of determinants. Our analysis was done on sixty-four data from sixteen psychiatric hospitals in Thailand under the Department of Mental Health since 2007 to 2010. Number of all staff (STAFF), number of beds (BED), number of out-patient visits (OPD), number of in-patient bed day (IPD), number of psychiatric nurse trainees (TRAIN), average length of stay (ALOS), location (Region), and level of hospital accreditation (HA) are collected as secondary data. From the data, we can answer the first question of variety of psychiatric hospitals that there is high variation in decision making units as observed by standard deviations in descriptive statistics as shown in Table 4.1. We also show trends in changing hospital structures by using STAFF/BED ratio for input combination in Figure 4.1. and Table 4.3.

In DEA analysis, we have done pooling analysis (n=64). It showed most decision making units had variable return to scale technical efficiency scores (TEVRS) between 0.46 - 1.00. There are only 2 hospitals located on the frontier (TE score=100%). The average pure technical efficiency score was 84% and average scale efficiency scores was 85%. In overall picture, the extra large hospital group (more than 500 beds) is higher pure technical efficiency score, while pure technical inefficiency was more prevalent in medium (90-150 beds) and small (60 beds) hospital. The small hospital (60 beds) is higher scale efficiency scores and the scale inefficiency is more in large hospitals (200-500 beds). The finding shows that no training group was higher level in both pure technical inefficiency and scale inefficiency scores. Mostly of the scale inefficiency pattern was decreasing return to scale.

Last technique in this study is to use regression analysis to see effects of each determinant on TEVRS, and this is analyzed by pooling all data as panel data. The determinants of OPDSTAFF, IPDBED and dummy of training activity show positive relationship at the level of 0.001 and the average length of stay shows significantly negative relationship at the level of 0.01

5.2. Limitation of this study

The limitations in this study are as follow.

For input information, lack of data of inputs such as number of doctors, number of nurses, and other staff make us to accumulate all staff into one variable as STAFF. Lacking of data about maintenance cost for represent the capital input is also our limitation.

For output information, lack of DRG-RW makes us cannot do weighting technique on IPD which weighted IPD will give more precise estimation than non-weighted one.

5.3. Recommendation for further study

For further study suggest to

- 1) Incorporate more data categories both inputs and outputs. Output weighting technique by using DRG-RW should be done before using the data in DEA model. As well as price should be used to make allocative efficiency measurement which gives better economic implications than technical efficiency one.

- 2) Compare efficiency measurement techniques such as stochastic frontier to the DEA.
- 3) Identify some hidden mechanisms of efficiency by interviewing to find the way for improve the hospital performance.
- 4) Identify the impact of re-allocation policies after implementation by using total factor productivity index.
- 5) Focus more on the effect of complexity of services or scope of services on the hospital efficiency.



ศูนย์วิจัยทรัพยากร
จุฬาลงกรณ์มหาวิทยาลัย

References

- Athanassopoulos, A.D., Gounaris, C., and Sissouras, A. A descriptive assessment of the production and cost efficiency of general hospitals in Greece. *Health Care Management Science* 2 (1999): 97-106.
- Banker, R.D. Estimating most productive scale size using data envelopment analysis. *European Journal of Operational Research* 17 (1984):35-44
- Banker, R.D., Charnes, A., and Cooper, W.W. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science* 30 (1984):1078-1092.
- Banker, R.D., Conrad, R.F., and Strauss, R.P. A comparative application of data envelopment analysis and translog methods: An illustrative study of hospital production. *Management Science* 32 (January 1986): 30-44.
- Chang, H.H. Determinants of hospital efficiency: The case of central government- owned hospitals in Taiwan. *Omega, International Journal of Management Science* 26 (1998): 307–317.
- Charnes, A., Cooper, W.W., and Rhodes, E. Measuring the efficiency of decision making Units. *European Journal of Operational Research* 2 (1978):429-444.
- Cheschossak, P. Financial Status of Psychiatric Hospital under Department of Mental Health: An Overview Analysis. KhonKaen: Department of Mental Health, Ministry of public health, 2004.
- Coelli, T.J. A guide to DEAP version 2.1: A data envelopment analysis (computer) program. *CEPA Working Papers* Armidale: University of New England

- Cooper, W.W., Seiford, L.M., and Tone, K. *Data envelopment analysis: A comprehensive text with models, applications, references and DEA-Solver Software*. Boston: Kluwer Academic Publishers, 2000.
- Gerrier, G.D., and Valdmanis, V. Rural hospital performance and its correlates. *The Journal of Productivity Analysis* 7 (1996):63-80.
- Grosskopf, S., and Valdmanis, V. Evaluating hospital performance with case-mix- adjusted outputs. *Medical Care* 31 (1993):525-532.
- Hadley, J., Zuckerman, S., and Iezzoni, L.I. Financial pressure and competition: Changes in hospital efficiency and cost-shifting behavior. *Medical Care* 34 (March 1996): 205-219.
- International Labour Organization. *A technical note to the government: Financing universal health care in Thailand*. 2004. 63
- Linna, M. Measuring hospital cost efficiency with panel data models. *Health Economics* 7 (1998): 415–427.
- Linna, M., Nordblad, A., Koivu, M. Technical and cost efficiency of oral health care provision in Finnish health centres. *Social Science & Medicine* 56 (2003): 343–353.
- Mahannirankul, S, et al. Efficiency of efficiency of Psychiatric Hospitals under Mental Health Department. Chiangmai.Suanprung Hospital. Department of Mental Health, Ministry of public health, 2003.
- Masiye, F. Investigating health system performance: An application of data envelopment analysis to Zambian hospitals. *BMC Health Services Research* 7 (2007): 58-68.
- Thailand. Ministry of Public Health. *Health Policy in Thailand*. Nonthaburi: Ministry of Public Health, 2007.

- Mongkol, A. An Overview Analysis of financial Status for the fiscal year 2004 of Thai Psychiatric Hospitals Under Department of Mental Health. KhonKaen: Department of Mental Health, Ministry of public health, 2005.
- Newhouse, J.P. Frontier estimation: How useful a tool for health economics?. *Journal of Health Economics* 13 (1994): 317-22.
- Orme, C. and Smith, P.C. The potential for endogeneity bias in data envelopment analysis. *Journal of the Operational Research Society* 47 (1996): 73-83.
- Ozcan, Y.A., and Luke, R.D. A national study of the efficiency of hospitals in urban markets. *Health Service Research* 27 (February 1993): 719–739.
- Rebba, V., and Rizzi, D. Measuring hospital efficiency through data envelopment analysis when policy-makers' preferences matter: An application to a sample of Italian NHS hospitals. *Working Papers* Department of Economics Ca' Foscari University of Venice, 2006
- Riedel, M., Hofmarcher, M.M., and Paterson, I. Measuring hospital efficiency in Austria: A DEA approach. *Health Care Management Science* 5 (2002): 7-14.
- Sexton, T.R., Leiken, A.M., Nolan, A.H., Liss, S., Hogan, A., Silkman, R.H. Evaluating managerial efficiency of Veterans Administration medical centers using data envelopment analysis. *Medical Care* 27 (December 1989):1175-1188.
- Sherman, H.D. Hospital efficiency measurement and evaluation: Empirical test of a new technique. *Med Care* 22 (October 1984):922-938.
- Skinner, J. What do stochastic frontier cost functions tell us about inefficiency?. *Journal of Health Economics* 13 (1994): 323-28.
- Smith, P.C. Model misspecification in data envelopment analysis. *Annals of Operations Research* 73 (1997): 233-52. 64

- Steinmann, L., Dittrich, G., Karmann, A., and Zweifel, P. Measuring and comparing the (in)efficiency of German and Swiss hospitals. *The European Journal of Health Economics* 3 (2004): 216-226.
- Takamura, T., and Tone, K. A Comparative site evaluation study for relocating Japanese government agencies out of Tokyo. *Socio-Economic Planning Sciences* 37 (2003): 85-102.
- Wagstaff, A. Estimating efficiency in the hospital sector: A comparison of three statistical cost frontier models. *Applied Economics* 21 (1989): 659-72.
- Wibulpolprasert, S., ed. *Thailand Health Profile 1997-1998*. Bangkok: Express Transportation Organization Printing Press, 2000.
- Zavras, A.I., Tsakos, G., Economou, C., Kyriopoulos, J. Using DEA to evaluate efficiency and formulate policy within a Greek national primary health care network. *Journal of Medical Systems* 4 (2002): 285-292.
- Zere, E., Mbeeli, T., Shangula, K., Mandlhate, C., Mutirua, K., Tjivambi, B., and Kapenambili, W. Technical efficiency of district hospitals: Evidence from Namibia using data envelopment analysis. *Cost Effectiveness and Resource Allocation* 4 (2006): 5-13.

ศูนย์วิทยทรัพยากร
จุฬาลงกรณ์มหาวิทยาลัย

Biography

Name: Miss Pimnida Koolsoontralai
Nationality: Thai
Country: Thailand
Education: Certification of Nursing
Nakhon Ratchasima Nursing College
Work: Khonkaen Rajanagarindra Psychiatric Hospital



ศูนย์วิทยทรัพยากร
จุฬาลงกรณ์มหาวิทยาลัย