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วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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TECHNICAL EFFICIENCY AND ITS DETERMINANTS OF REGIONAL HOSPITALS IN THAILAND

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A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science Program in Health Economics and Health Care Management
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การศึกษานี้มีวัตถุประสงค์เพื่อศึกษาประสิทธิภาพทางเทคนิคและปัจจัยที่กำหนดประสิทธิภาพทางเทคนิคของโรงพยาบาลศูนย์ทั้งหมดในประเทศไทย โดยใช้ข้อมูลของโรงพยาบาลศูนย์ทั้งหมด 25 แห่งในปี พ.ศ. 2550-2551 จำนวน 50 หน่วยประเมิน

ขั้นแรก การวัดประสิทธิภาพทางเทคนิคโดยการวิเคราะห์แบบ Data Envelopment Analysis ผลการวิเคราะห์พบว่ามี 31 จาก 50 หน่วยประเมินที่มีค่าประสิทธิภาพรวมสูงสุด และมีค่าต่ำสุดเท่ากับ 0.810 พบมี 36 จาก 50 หน่วยประเมินที่มีค่าประสิทธิภาพทางเทคนิคที่แท้จริงสูงสุด และมีค่าต่ำสุดเท่ากับ 0.817 และพบมี 32 จาก 50 หน่วยประเมินที่มีค่าประสิทธิภาพด้านการจัดสรรสูงสุด และมีค่าต่ำสุดเท่ากับ 0.889 ค่าประสิทธิภาพทั้งสามมีค่าเฉลี่ยมัธยฐานเท่ากับ 1.000 และในกลุ่มที่ไม่มีประสิทธิภาพทางขนาดพบว่า เป็นแบบผลตอบแทนที่เพิ่มขึ้นเป็นส่วนใหญ่ ทางด้านแพทยศาสตร์ศึกษาจากผลการศึกษาพบว่า โรงพยาบาลศูนย์ที่มีการสอนมีประสิทธิภาพสูงกว่าที่โรงพยาบาลศูนย์ที่ไม่มีการสอน และกลุ่มโรงพยาบาลศูนย์ที่มีทั้งการสอนนักศึกษาแพทย์ชั้นคลินิกและสอนแพทย์ประจำบ้านเป็นกลุ่มที่มีประสิทธิภาพสูงสุด

ขั้นที่สอง การศึกษาปัจจัยที่กำหนดประสิทธิภาพทางเทคนิคของโรงพยาบาลศูนย์ทั้งหมด โดยใช้เทคนิคการวิเคราะห์สมการถดถอยแบบ ordinary least square estimation พบว่า อัตราส่วนจำนวนเตียงต่อแพทย์และอัตราส่วนจำนวนบุคลากรอื่นต่อแพทย์ลดลง 1 หน่วย ค่าประสิทธิภาพที่แท้จริงจะเพิ่มขึ้น 0.029290 และ 0.008336 หน่วยตามลำดับ ในขณะที่อัตราส่วนของจำนวนพยาบาลต่อแพทย์และอัตราการฝึกอบรมแพทย์เพิ่มพูนทักษะให้จบต่ออาจารย์แพทย์เพิ่มขึ้น 1 หน่วย ค่าประสิทธิภาพที่แท้จริงจะเพิ่มขึ้น 0.023639 และ 0.208326 หน่วยตามลำดับ สำหรับค่าประสิทธิภาพด้านการจัดสรรพบว่า อัตราส่วนของจำนวนครั้งของการนอนของผู้ป่วยในคูณด้วยค่าเฉลี่ยแบบถ่วงน้ำหนักของกลุ่มโรคตามการวินิจฉัยต่อแพทย์มีจำนวนเพิ่มขึ้น 1 หน่วย ค่าประสิทธิภาพด้านการจัดสรรจะเพิ่มขึ้น 0.000110 หน่วย สำหรับการประยุกต์ใช้ในการกำหนดนโยบาย หน่วยประเมินที่ไม่มีประสิทธิภาพทางขนาดส่วนใหญ่เป็นแบบผลตอบแทนที่เพิ่มขึ้น ดังนั้นการเพิ่มขนาดของโรงพยาบาลเป็นสิ่งที่ควรกระทำเพื่อให้มีระดับประสิทธิภาพเชิงขนาดที่ดียิ่งขึ้น ทั้งนี้ควรศึกษารายละเอียดเพิ่มเติมในแต่ละแห่ง และควรสนับสนุนให้มีการสอนด้านแพทยศาสตร์ศึกษาในโรงพยาบาลศูนย์ที่มีศักยภาพ.

สาขาวิชา เศรษฐศาสตร์สาธารณสุขและการจัดการบริการสุขภาพ ลายมือชื่อนิสิต ....
ปีการศึกษา 2552 ลายมือชื่อ อ.ที่ปรึกษาวิทยานิพนธ์หลัก ....
ลายมือชื่อ อ.ที่ปรึกษาวิทยานิพนธ์ร่วม ....

5285752929: MAJOR HEALTH ECONOMICS AND HEALTH CARE MANAGEMENT
KEYWORDS: TECHNICAL EFFICIENCY/ DATA ENVELOPMENT ANALYSIS/ REGIONAL HOSPITAL/ THAILAND

WICHIAN THIANJARUWATTHANA: TECHNICAL EFFICIENCY AND ITS DETERMINANTS OF REGIONAL HOSPITALS IN THAILAND. THESIS ADVISOR: ASSSOC. PROF. PONGSA PORNCHAIWISESKUL, Ph. D., THESIS CO-ADVISOR: PROF. PIROM KAMOL-RATANAKUL, M.D., 172 pp.

Output-orientated Data Envelopment Analysis was used to measure the technical efficiency of 25 regional hospitals in Thailand from 2007-2008 as 50 decision making units (DMUs). The results revealed, there were 31 efficient DMUs from 50 DMUs for overall technical efficiency scores and a minimum was 0.810. There were 36 efficient DMUs from 50 DMUs for pure technical efficiency scores and a minimum was 0.817. For scale efficiency scores, there were 32 efficient DMUs from 50 DMUs and a minimum was 0.889. In addition, medians of all three scores were 1.000. Most of patterns of scale inefficiency were the increasing return to scale (irs:drs = 14:5). In medical education services, the results found teaching hospitals were more efficient than non-teaching hospitals and a combined undergraduate and postgraduate teaching hospital was the most efficient group.

The next step was to identify the determinants of hospital efficiency with regression analysis using ordinary least squares (OLS). The results revealed if beds-physician ratio and other personnel-physician ratio decreased one unit, pure technical efficiency scores tended to increase 0.029290 and 0.008336 units respectively. If nurses-physician ratio and trained interns-physician staff ratio increased one unit, pure technical efficiency scores tended to increase 0.023639 and 0.208326 units respectively. And the most influential explanatory variable of pure technical efficiency scores was a trained interns-physician staff ratio. For scale efficiency scores, if in-patient visits adjusted with relative weight of DRG per physician increased one unit, scale efficiency scores tended to increase 0.000110 units. All above information could be used for policy makers in health sector and hospital managers improve the inefficient regional hospitals in proper direction such as most of patterns of scale inefficiency were the increasing returns to scale which can be improved through up-sizing and should supported medical education in regional hospitals which have competency. In addition, the details of each inefficient hospital should be explored and analyzed with the information from DEA and regression analyses.

Field of Study: Health Economics and Health Care Management Student's Signature.......................

Academic Year: 2009 Advisor's Signature.......................

Co-Advisor's Signature P. Kamolratanakul

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LIST OF ABBREVIATIONS

BCC	Banker-Charnes-Cooper model
CCR	Charnes-Cooper-Rhodes model
CPIRD	Collaborative Project to Increase Production of Rural Doctor
CSMBS	Civil Servant Medical Benefit Scheme
DEA	Data envelopment analysis
DMU	Decision making unit
DRG	Diagnostic related group
DRS	Decreasing return to scale
HA	Hospital Accreditation
IRS	Increasing return to scale
MoPH	Ministry of Public Health
OLS	Ordinary least squares
SBM	Slacks-Based Measure model
SE	Scale efficiency
SSS	Social Security Scheme
TE	Technical efficiency
TECRS	Technical efficiency under constant return to scale
TEVRS	Technical efficiency under variable return to scale
UC	Universal coverage scheme

CHAPTER I

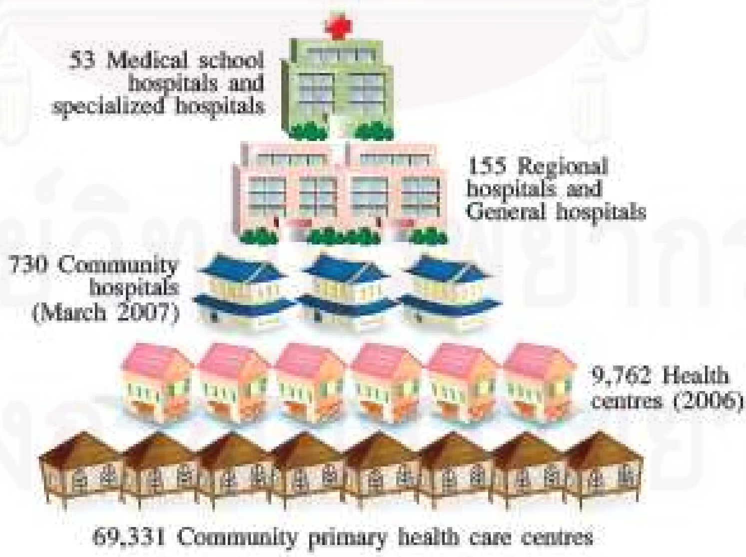
INTRODUCTION

1.1 Problem and its significance

Regional hospitals in Thailand are tertiary or super-tertiary public hospitals which have main functions not only tertiary health care service, but also primary and secondary health care services. Some regional hospitals are excellent centers in some advance services such as cardiac excellent center, cancer excellent center, and trauma excellent center. They can joint with some excellent centers depending on their performances. Quality in health care service is one issue that must be concerned and most public hospitals in Thailand choose Thai Hospital Accreditation for quality standard benchmark but it is not compulsory.

Health care demand increases more and more in all levels of health care providers; at the same time, the Thai health system has been expanded to provide health care services at all levels from primary to tertiary. Every district had a community hospital, so there were over 700 community hospitals. Tertiary care liked regional hospital consists of health facilities which were fully equipped with expensive medical instruments, resources and specialized staff to provide sophisticated medical services and treatment. There were 155 regional and general hospitals in year 2007. And super-tertiary care liked Medical school hospitals and specialized hospitals had only 53 hospitals in year 2007 as Figure 1-1 (Churnrurtai Kanchanachitra et al., 2009). So the more complicate health care service was the less numbers of hospitals like pyramid.

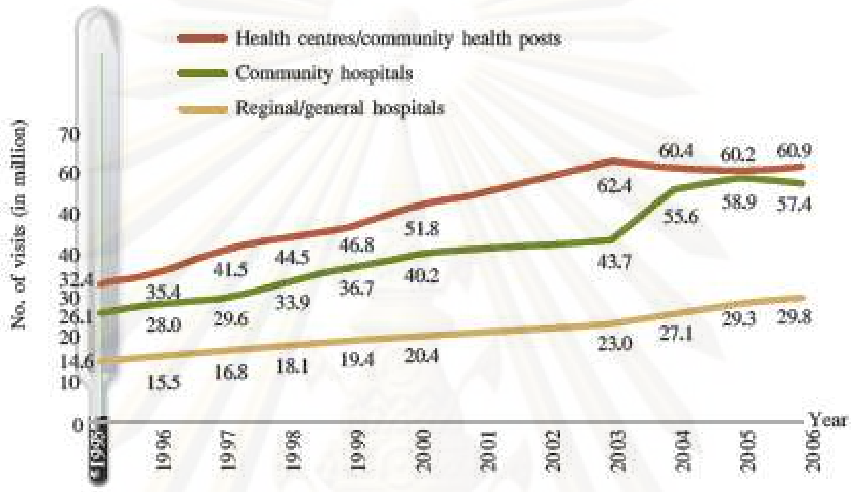
Figure 1-1 Type of health facility in the public sector, 2007
(excluding Bangkok)



SOURCE: Churnrurtai Kanchanachitra et al., (2009): 11

Statistics indicated that community health centers and community hospitals were the most popular source of health care especially primary health care service. The numbers of out-patient visits of health centers; community, general and regional hospitals increased every year from 1996 to 2006 and the numbers of out-patient visits of health centers were more than community hospitals, and more than general and regional hospitals as Figure 1-2 (Churnrurtai Kanchanachitra et al., 2009).

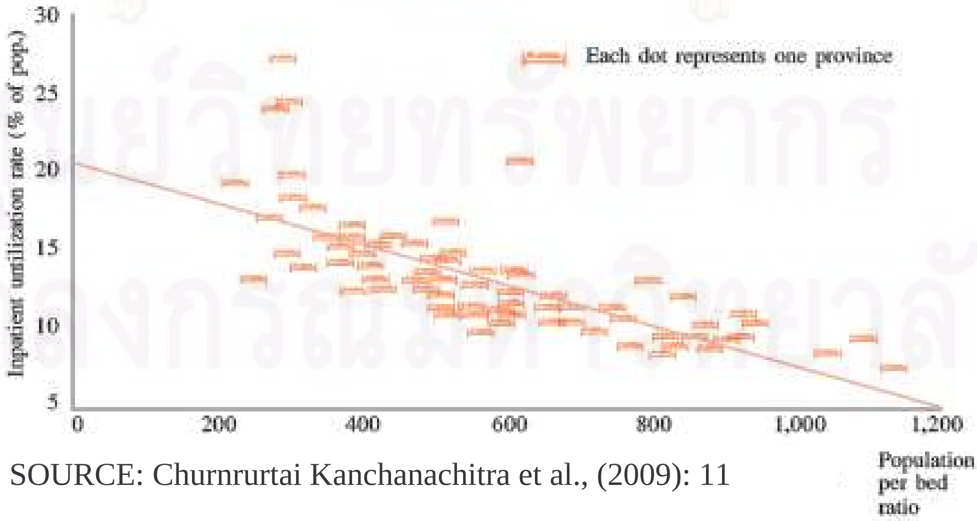
Figure 1-2 Trends of out-patients visits by level of MOPH health facilities, 1995-2006



SOURCE: Churnrurtai Kanchanachitra et al., (2009): 11

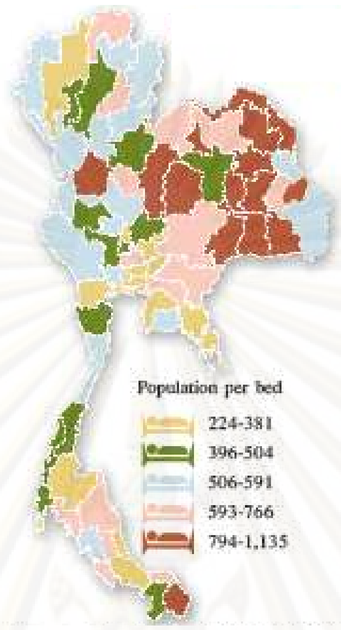
The provinces with more beds per the population will have more in-patients, while those provinces with few beds will also have fewer in-patients. In other word, access to health services was better in the former provinces than the latter, indicating to some extent the existence of inequities in access to health care in year 2004 as Figure 1-3, 1-4 below (Churnrurtai Kanchanachitra et al., 2009).

Figure 1-3 Relationship between the rate of in-patient service utilization and population/bed ratios at provincial level, 2004



SOURCE: Churnrurtai Kanchanachitra et al., (2009): 11

Figure 1-4 Population per bed ratios by province, 2004



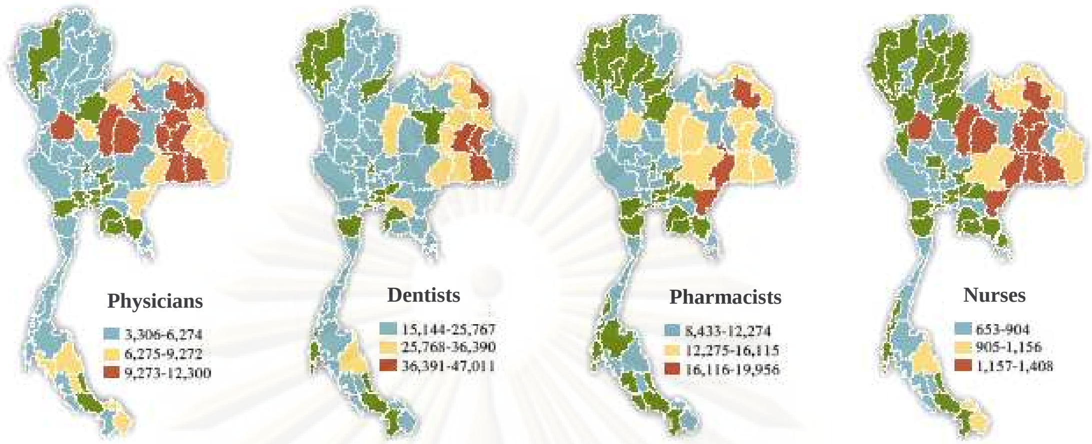
SOURCE: Churnrurtai Kanchanachitra et al., (2009): 11

The production of medical staffs increased more in all levels especially physicians and dentists as Figure 1-5, but the distribution of human resources for health had been found inequitable as Figure 1-6, particularly the inequitable distribution between rural and urban areas. So there was shortage of human resources for health in rural areas. The poor and remote areas in the Northeast of Thailand where were the majority of the country resides having the highest ratio of population per one health personnel (Churnrurtai Kanchanachitra et al., 2009).

Figure 1-5 Annual resignation rate of health workforce as % of total new entry in 1999-2005

SOURCE: Churnrurtai Kanchanachitra et al., (2009): 13

Figure 1-6 Geographical distribution of health workforce in 2007



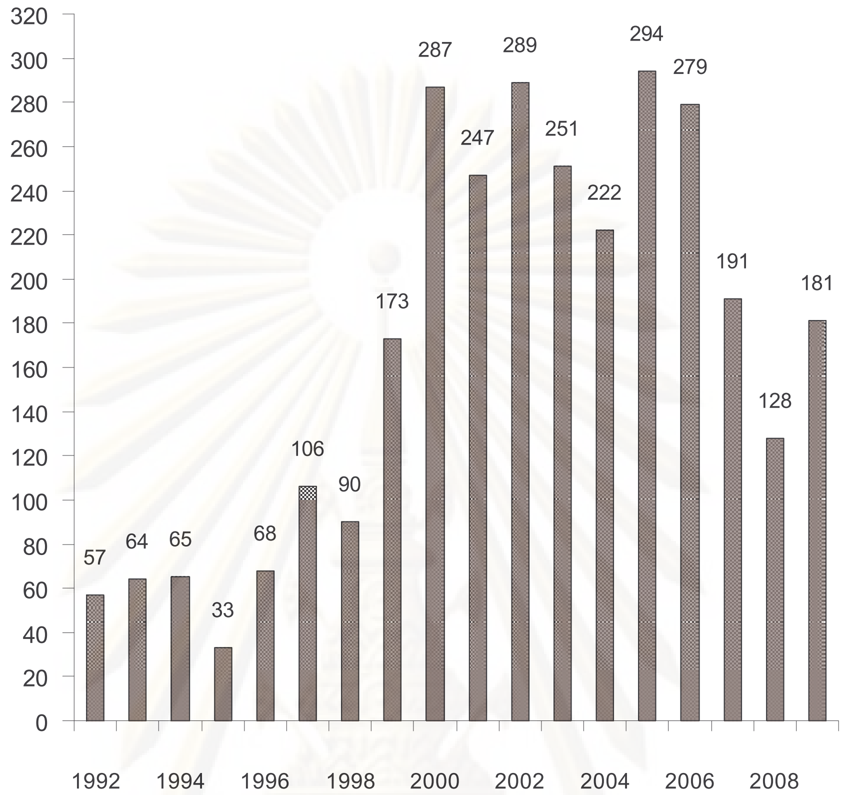
SOURCE: Churnrurtai Kanchanachitra et al., (2009): 13

The physician shortage in Thailand was currently the significant problem threatening the Thai health system. The geographical misdistribution of physicians was reinforced by the attraction of private practice. In order to limit the "brain-drain" problem of physicians from the public to private sector, a special non-private-practice allowance of 10,000 Baht/month for physician was introduced in 1993 as an incentive for physicians in the public sector to devote all their professional time to the public sector (Nishiura et al., 2004; Thaworn Sakunphanit, 2006). The brain-drain problem in regional hospitals improves but it still persists. The Ministry of Public Health allows only specialists and sub-specialists can practice in regional hospitals and the production of specialists and sub-specialists spend 3-5 years. So the rate of increasing of physicians in regional hospitals is slower than the rate of increasing of demand in health care services of regional hospitals.

Thailand faced the problems of shortage of physicians in rural areas. The Ministry of Public Health had policy to increase the number of physicians by pushing the potential general and regional hospitals to collaborate with the Faculty of Medicine in the universities to produce the qualified physicians. However, the quality control in process of physician production was strictly examined to qualify the performance of new physicians to public. Most regional hospitals must develop medical education centers in hospitals for undergraduate level to teach the clinical years of medical student (4^{th}, 5^{th}, and 6^{th} years); in addition, some regional hospitals can develop themselves or collaborate with the Faculty of Medicine in the universities to produce some postgraduate levels (specialist and sub-specialist training programs).

Health care reform in Thailand (starting in 1999), new laws and medical regulations contributed to improve the quality of health care; in contrast, some issues especially patient right created more expectation and increased medical claims and sue in year 1999-2005 as graph in Figure 1-7. So many patients were referred to regional hospitals and brought huge burden to them.

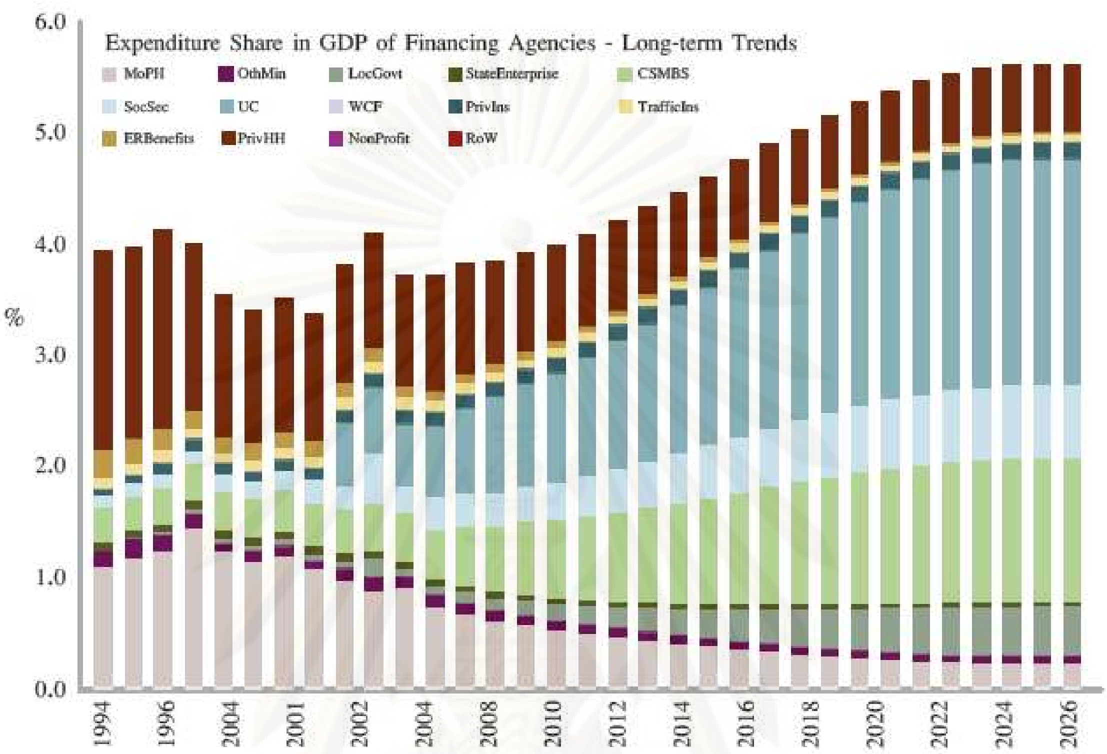
Figure 1-7 The numbers of claimed physicians since 1992-2009



SOURCE: Bureau of Medical Council of Thailand, 2009

During the previous decade, health expenditure in Thailand increased dramatically. After the implementation of Universal Coverage Scheme, health expenditure from Universal Coverage Scheme increased significantly as Figure 1-8 while Gross Domestic Product (GDP) stabilized at 3.5% by 2005 (Churnrurtai Kanchanachitra et al., 2009). If health care demands still increase more and more while the government revenue and budget subsidization to health care providers does not increase in the same rate, the financial problems in health care providers will increase in the future.

Figure 1-8 Long term forecast of Total Health Expenditure, as percent of Gross Domestic Product (GDP) by sources of finance



SOURCE: Churnrurtai Kanchanachitra et al., (2009): 19

MOPH = Minister of Public Health
OthMin = Other Ministries
LocGovt = Local Government
StateEnterprise = State Enterprise
CSMBS = Civil Servant Medical Benefit Scheme
SocSec = Social Security Scheme
UC = Universal Health Care Coverage
MOPH = Minister of Public Health
OthMin = Other Ministries
LocGovt = Local Government
StateEnterprise = State Enterprise
CSMBS = Civil Servant Medical Benefit Scheme
SocSec = Social Security Scheme
UC = Universal Health Care Coverage

Among many burdens of these regional hospitals, other problems include the limited resources in supply side of health care services such as insufficient medical personnel in all levels, and financial sustainability in long-term; furthermore, progressive over demand in health care services. So it is not easy for these regional hospitals to survive in the future except they can efficiently manage.

Data Envelopment Analysis (DEA) is the most popular technique which uses the concept of linear programming to evaluate the efficiency score of many businesses by construction of a non-parametric piecewise surface, or frontier, over the data to calculate efficiencies relative to this surface. DEA can measure the hospital efficiency of multiple inputs and outputs model (Bhat, Verma, & Reuben, 2001).

The regression analysis bases on statistic testing and estimation when this technique is used together with DEA to provide more details in each factor that influences the efficiency score. Decision making units (DMUs) are the units using appropriate portion of inputs to produce outputs to compare the efficiency (Kornpob Bhirombhakdi, 2008).

In Thailand, some regional hospitals try to survive with good performance of some excellent centers for super-tertiary care, pass in further level of hospital accreditation, and collaboration with medical education in undergraduate level or/and postgraduate level or both levels. It is not easy to maintain these conditions in the same time under budget constraint and a lot of burdens in each service so I am interested in studying technical efficiency of regional hospitals in Thailand. There are some studies about technical efficiency of hospitals in Thailand, and most of them studied about all levels of hospitals, provincial hospitals, medium-sized community hospitals, or university hospitals. However, my study concentrates on only regional hospitals because they have similar context and can fairly compare their results together; in addition, compare with the previous studies.

1.2 Research questions

The interesting questions want to know the technical efficiency of all regional hospitals in Thailand as the whole picture and the technical efficiency of individual regional hospitals. The other interesting questions want to know the factors affecting on the efficiency of regional hospitals or determinants of hospital efficiency; in addition, the magnitude and direction of each determinant affect the technical efficiency of regional hospitals. So the research questions are as following:

Primary research question

- What are the levels of technical efficiency scores of regional hospitals in Thailand?

Secondary research question

- What explanatory variables do affect the efficiency scores of regional hospitals?

1.3 Research objectives

The first question measures the hospital efficiency of the whole picture and the technical efficiency of individual regional hospitals in terms of technical and scale efficiency scores. The second question determines the factors affecting on the technical and scale efficiency scores of regional hospitals or their determinants of hospital efficiency. Some determinants will directly affect the efficiency scores of regional hospitals but some determinants will inversely affect the efficiency scores of these hospitals and the question wants to know which determinant is the most influential factor of the efficiency scores of regional hospitals or the magnitude of each factor of the efficiency scores. So the research objectives are as following:

General objective

- To measure the technical efficiency of regional hospitals in Thailand

Specific objective

- To identify the factors affecting on the efficiency of regional hospitals (determinants of hospital efficiency)

1.4 Scope of the study

Evaluation of technical efficiency of all regional hospitals in Thailand plays attention to two main activities; health care service and medical education service. Secondary panel data have been collected since 2007-2008. For health care service, this study focuses on the out-patient visits and in-patient visits which are the outputs of health care service. For medical education service, this study focuses on both undergraduate (graduated medical student) and postgraduate levels (trained interns and trained residents) which are the outputs of medical education service.

1.5 Possible benefits

Potential beneficiaries of this study may include: Ministry of Public Health, regional hospitals, scholars involved in health policy and economic research. This study allows us to know the hospital efficiency performance of regional hospitals in Thailand. It reveals the efficiency profile of the whole picture, the individual regional hospital, the best practice regional hospitals (the most efficient as the good models) and the inefficient hospitals. It also informs the factors affecting on the efficiency of regional hospitals (determinants of hospital efficiency).

The result of this study is useful for:

1. The policy makers in health sector use this information to improve the inefficient hospitals to more efficient in manner by downsizing or upsizing of some inefficient hospitals.

2. The hospital administrators use this information to improve their hospitals to more efficient in the right direction and are able to use the most efficient hospitals as the model for improvement.

CHAPTER II

LITERATURE REVIEW

2.1 Theoretical Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a relatively new data oriented approach for evaluating the performance of a set of peer entities called Decision Making Units (DMUs) which convert multiple inputs into multiple outputs. The definition of a DMU is generic and flexible. Recent years have seen a great variety of applications of DEA for use in evaluating the performances of many different kinds of entities engaged in many different activities, in many different contexts, and in many different countries. These DEA applications have used DMUs of various forms to evaluate the performance of entities, such as hospitals, universities, cities, business firms, and others, including the performance of countries, regions, etc. Because it requires very few assumptions, DEA has opened up the possibilities for use in cases which have been resistant to other approaches because of the complex (often unknown) nature of the relations between the multiple inputs and multiple outputs involved in DMUs.

As pointed out by Cooper, Seiford and Tone (2000), DEA has also been used to supply new insights into activities (and entities) that have previously been evaluated by other methods. For instance, the studies of benchmarking practices with DEA have identified numerous sources of inefficiency in some of the most profitable firms – firms that had served as benchmarks by reference to this (profitability) criterion – and this has provided a vehicle for identifying better benchmarks in many applied studies. A use of DEA has suggested reconsideration of previous studies of the efficiency with which pre- and post-merger activities have been conducted in banks that were studied by DEA.

Since DEA was first introduced in 1978, researchers in a number of fields have quickly recognized that it is an excellent and easily used methodology for modeling operational processes for performance evaluations. This has been accompanied by other developments. For instance, Zhu (2002) provided a number of DEA spreadsheet models that could be used in performance evaluation and benchmarking. DEA's empirical orientation and the absence of a need for the numerous *a priori* assumptions that accompany other approaches (such as standard forms of statistical regression analysis) have resulted in its use in a number of studies involving efficient frontier estimation in the governmental and nonprofit sector, and in the private sector.

In the originating study, Charnes, Cooper, and Rhodes (1978) described DEA as a 'mathematical programming model applied to observational data that provides a new way of obtaining empirical estimates of relations – such as the production functions and/or efficient production possibility surfaces – that are cornerstones of modern economies'.

Formally, DEA is a methodology directed to frontiers rather than central tendencies. Instead of trying to fit a regression plane through the *center* of the data as in statistical regression; for example, one 'floats' a piecewise linear surface to rest on top of the observations. Because of this perspective, DEA proves particularly adept at uncovering relationships that remain hidden from other methodologies. For instance, consider which one is “efficiency” or; more generally, which DMUs are more efficient than other DMUs. This is accomplished in a straightforward manner by DEA without requiring explicitly formulated assumptions and variations with various types of models such as in linear and nonlinear regression models.

Relative efficiency in DEA accords with the following definition which has the advantage of avoiding the need for assigning a priori measures of relative importance to any input or output,

Definition 1.1 (Efficiency – Extended Pareto-Koopmans Definition): Full (100%) efficiency is attained by any DMU if and only if none of its inputs or outputs can be improved without worsening some of its other inputs or outputs.

In most management or social science applications the theoretically possible levels of efficiency will not be known. The preceding definition is therefore replaced by emphasizing its uses with only the information that is empirically available as in the following definition:

Definition 1.2 (Relative Efficiency): A DMU is to be rated as fully (100%) efficient on the basis of available evidence if and only if the performances of other DMUs does not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs.

This definition avoids the need for recourse to prices or other assumptions of weights which are supposed to reflect the relative importance of the different inputs or outputs. It also avoids the need for explicitly specifying the formal relations that are supposed to exist between inputs and outputs. This basic kind of efficiency, referred to as “technical efficiency” in economics can be extended to other kinds of efficiency when data such as prices, unit costs, etc., are available for use in DEA (Cooper, Seiford, & Zhu, 2004: 1-3).

2.1.1 CCR DEA model

To allow for applications to a wide variety of activities, Decision Making Unit (=DMU) is used to refer to any entity that is to be evaluated in terms of its abilities to convert inputs into outputs. These evaluations can involve governmental agencies, not-for-profit organizations, and business firms. The evaluation can also be directed to educational institutions and hospitals for which comparative evaluations of their performance are to be made.

Assume that there are n DMUs to be evaluated. Each DMU consumes varying amounts of m different inputs to produce s different outputs. Specifically, DMU_j consumes amount x_{ij} of input i and produces amount y_{rj} of output r. In addition, assume that $x_{ij} \geq 0$ and $y_{rj} \geq 0$ and each DMU has at least one positive input and one positive output value.

The “ratio-form” of DEA is introduced by Charnes, Cooper, and Rhodes. The ratio of outputs to inputs is used to measure the relative efficiency of the $DMU_{j} = DMU_o$ to be evaluated relative to the ratios of all of the $j = 1, 2,\ldots, n$ DMU_j. The Charnes-Cooper-Rhodes model (CCR) construction can be interpreted as the reduction of the multiple-output /multiple-input situation (for each DMU) to that of a single 'virtual' output and 'virtual' input. For a particular DMU the ratio of this single virtual output to single virtual input provides a measure of efficiency that is a function of the multipliers. In mathematical programming parlance, this ratio; which is to be maximized, forms the objective function for the particular DMU being evaluated, so that symbolically

$$\max h_o(u,v) = \Sigma_r u_r y_{ro} / \Sigma_i v_i x_{io} \tag{2.1}$$

where the variables are the u_r's and the v_i's and the y_{ro}'s and x_{io}'s are the observed output and input values, respectively, of DMU_o, the DMU to be evaluated. Of course, without further additional constraints (developed below) (2.1) is unbounded.

A set of normalizing constraints (one for each DMU) reflects the condition that the virtual output to virtual input ratio of every DMU, including $DMU_{j=}$ DMU_o, must be less than or equal to unity. The mathematical programming problem may be stated as

$$\begin{aligned} &\max h_o(u,v) = \Sigma_r u_r y_{ro} / \Sigma_i v_i x_{io} \\ &\text{subject to} \\ &\Sigma_r u_r y_{rj} / \Sigma_i v_i x_{ij} \leq 1 \text{ for } j = 1,\ldots, n, \\ &u_r, v_i \geq 0 \text{ for all } i \text{ and } r. \end{aligned} \tag{2.2}$$

Remark: A fully rigorous development would replace $u_r, v_i \geq 0$ with

$\dfrac{u_r}{\sum_{i=1}^{m} v_i x_{io}}, \dfrac{u_r}{\sum_{i=1}^{m} v_i x_{io}} \geq \varepsilon > 0$ where ε is a non-Archimedean element smaller than any positive real number. This condition guarantees that solutions will be positive in these variables. It also leads to the $\varepsilon > 0$ in (2.6) which, in turn, leads to the 2nd stage optimization of the slacks as in (2.10).

The above ratio form yields an infinite number of solutions; if (u^*, v^*) is optimal, so $(\alpha u^*, \alpha v^*)$ is also optimal for $\alpha > 0$. However, the transformation developed by Charnes and Cooper (1962) for linear fractional programming selects a representative solution [i.e., the solution (u, v) for which $\Sigma_{i=1}^{m} v_i x_{io} = 1$ and yields the equivalent linear programming problem in which the change of variables from (u, v) to (μ, v) is a result of the Charnes-Cooper transformation,

$$\begin{aligned} &\max z = \sum_{r=1}^{s} \mu_r y_{ro} \\ &\text{subject to} \\ &\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \\ &\sum_{i=1}^{m} v_i x_{io} = 1 \\ &\mu_r, v_i \geq 0 \end{aligned} \tag{2.3}$$

for which the LP dual problem is

$$
\begin{aligned}
&\theta^* = \min \theta \\
&\text{subject to} \\
&\sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{io} \qquad i = 1,2,\dots,m; \\
&\sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{ro} \qquad r = 1,2,\dots,s; \\
&\lambda_j \ge 0 \qquad j = 1,2,\dots,n.
\end{aligned} \tag{2.4}
$$

This last model, (2.4), is sometimes referred to as the "Farrell model" because it is the one used in Farrell (1957). In the economics portion of the DEA literature, it is said to conform to the assumption of "strong disposal" because it ignores the presence of non-zero slacks. In the operations research portion of the DEA literature, this is referred to as "weak efficiency."

By virtue of the dual theorem of linear programming, $z^* = \theta^*$. One can solve say (2.4), to obtain an efficiency score. Because of setting $\theta = 1$ and $\lambda_k^* = 1$ with $\lambda_k^* = \lambda_o^*$ and all other $\lambda_j^* = 0$, a solution of (2.4) always exists. Moreover this solution implies $\theta^* \le 1$. The optimal solution, θ^*, yields an efficiency score for a particular DMU. The process is repeated for each DMU_j i.e., solve (2.4), with $(X_o, Y_o) = (X_k, Y_k)$ where (X_k, Y_k) represent vectors with components x_{ik}, y_{rk} and, similarly (X_o, Y_o) has components x_{ok}, y_{ok}. DMUs for which $\theta^* < 1$ are inefficient, while DMUs for which $\theta^* = 1$ are boundary points.

Some boundary points may be "weakly efficient" because of nonzero slacks. This may appear to be worrisome because alternate optima may have non-zero slacks in some solutions, but not in others. The slacks are taken to their maximal values in the following linear program.

$$
\begin{aligned}
&\max \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \\
&\text{subject to} \\
&\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta^* x_{io} \qquad i = 1,2,\dots,m; \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \qquad r = 1,2,\dots,s; \\
&\lambda_j, s_i^-, s_r^+ \ge 0 \ \forall i, j, r
\end{aligned} \tag{2.5}
$$

where the choices of s_i^- and s_r^+ do not affect the optimal θ^* which is determined from model (2.4).

These developments lead to the following definition based upon the "relative efficiency" definition 1.2 which was given in section 1 above.

Definition 1.3 (DEA Efficiency): The performance of DMU_o is fully (100%) efficient if and only if both (i) $\theta^* = 1$ and (ii) all slacks $s_i^{-*} = s_r^{+*} = 0$.

Definition 1.4 (Weakly DEA Efficient): The performance of DMU_o is weakly efficient if and only if both (i) $\theta^* = 1$ and (ii) $s_i^{-*} \ne 0$ and/or $s_r^{+*} \ne 0$ for some i and r in some alternate optima.

$$\begin{aligned}
&\min \theta - \varepsilon\Big(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\Big) \\
&\text{subject to} \\
&\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io} \qquad i = 1,2,\ldots,m; \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - s_i^+ = y_{ro} \qquad r = 1,2,\ldots,s; \\
&\lambda_j, s_i^-, s_r^+ \geq 0 \ \forall i, j, r
\end{aligned} \tag{2.6}$$

where the s_i^- and s_r^+ are slack variables used to convert the inequalities in (2.4) to equivalent equations. Here $\varepsilon > 0$ is a so-called non-Archimedean element defined to be smaller than any positive real number. This is equivalent to solving (2.4) in two stages by first minimizing θ, then fixing $\theta = \theta^*$ as in (2.2), where the slacks are to be maximized without altering the previously determined value of $\theta = \theta^*$. Formally, this is equivalent to granting "preemptive priority" to the determination of θ^* in (2.3). In this manner, the fact that the non-Archimedean element ε is defined to be smaller than any positive real number is accommodated without having to specify the value of ε.

Alternately, one could have started with the output side and considered instead the ratio of virtual input to output. This would reorient the objective from max to min, as in (2.2), to obtain

$$\begin{aligned}
&\text{Min } \textstyle\sum_i v_i x_{io} / \sum_r u_r y_{ro} \\
&\text{Subject to} \\
&\textstyle\sum_i v_i x_{ij} / \sum_r u_r y_{rj} \geq 1 \text{ for } j = 1, \ldots, n, \\
&u_r, v_i \geq \varepsilon > 0 \text{ for all } i \text{ and } r.
\end{aligned} \tag{2.7}$$

where $\varepsilon > 0$ is the previously defined non-Archimedean element.

Again, the Charnes-Cooper (1962) transformation for linear fractional programming yields model (2.8) (multiplier model) below, with associated dual problem, (2.9) (envelopment model), as in the following pair,

$$\begin{aligned}
&\min q = \sum_{i=1}^{m} v_i x_{io} \\
&\text{subject to} \\
&\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0 \\
&\sum_{r=1}^{s} \mu_r y_{ro} = 1 \\
&\mu_r, v_i \geq \varepsilon, \quad \forall r, i
\end{aligned} \tag{2.8}$$

$$\begin{aligned}
&\max \phi + \varepsilon\Big(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\Big) \\
&\text{subject to} \\
&\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{io} \quad i = 1,2,\ldots,m; \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \phi y_{ro} \ \ r = 1,2,\ldots,s; \\
&\lambda_j \geq 0 \qquad\qquad j = 1,2,\ldots,n.
\end{aligned} \tag{2.9}$$

A model with an output oriented objective is used as contrasted with the input orientation in (2.6). However, as before, model (2.9) is calculated in a two-stage process. The first stage calculates ϕ^* by ignoring the slacks. Then the second stage optimizes the slacks by fixing ϕ^* in the following linear programming problem,

$$\begin{aligned}
&\max \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \\
&\text{subject to} \\
&\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{io} \qquad i = 1,2,\ldots,m; \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \phi^* y_{ro} \qquad r = 1,2,\ldots,s; \\
&\lambda_j \ge 0 \qquad j = 1,2,\ldots,n.
\end{aligned} \tag{2.10}$$

Then the previous input-oriented definition of DEA efficiency is modified to the following output-oriented version.

Definition 1.5: DMU_o is efficient if and only if $\phi^* = 1$ and $s_i^{-*} = s_r^{+*} = 0$ for all i and r. DMU_o is weakly efficient if $\phi^* = 1$ and $s_i^{-*} \neq 0$ and (or) $s_r^{+*} \neq 0$ for some i and r in some alternate optima.

Table 2-1 presents the CCR model in input- and output-oriented versions, each in the form of a pair of dual linear programs.

Table 2-1 CCR DEA model

Envelopment model	Multiplier model
Input-oriented	
$\min \theta - \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+)$	$\max z = \sum_{r=1}^{s} \mu_r y_{ro}$
subject to	subject to
$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io} \quad i = 1,2,\ldots,m;$	$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} \nu_i x_{ij} \le 0$
$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \quad r = 1,2,\ldots,s;$	$\sum_{i=1}^{m} \nu_i x_{io} = 1$
$\lambda_j \ge 0 \quad j = 1,2,\ldots,n.$	$\mu_r, \nu_i \ge \varepsilon > 0$
Output-oriented	
$\max \phi + \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+)$	$\min q = \sum_{i=1}^{m} \nu_i x_{io}$
subject to	subject to
$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{io} \quad i = 1,2,\ldots,m;$	$\sum_{i=1}^{m} \nu_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \ge 0$
$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \phi y_{ro} \quad r = 1,2,\ldots,s;$	$\sum_{r=1}^{s} \mu_r y_{ro} = 1$
$\lambda_j \ge 0 \quad j = 1,2,\ldots,n.$	$\mu_r, \nu_i \ge \varepsilon > 0$

SOURCE: Cooper, Seiford, & Zhu, (2004): 13

These are known as CCR (Charnes, Cooper, Rhodes) models. If the constraint $\Sigma_{i=1}^{n} \lambda_j = 1$ is adjoined, they are known as BCC (Banker, Charnes, Cooper) models. The added constraint introduces an additional variable, μo into the (dual) multiplier problems. This extra variable makes it possible to effect returns-to-scale evaluations (increasing, constant and decreasing). So the BCC model is also referred to as the VRS (Variable Returns to scale) model and distinguished form the CCR model which is referred to as the CRS (Constant Returns to Scale) model (Cooper, Seiford, & Zhu, 2004: 8-14).

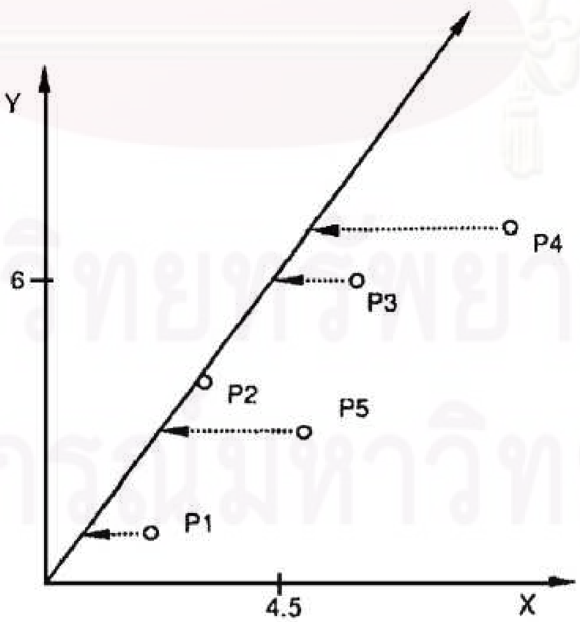
An inefficient DMU can be made more efficient by projection onto the frontier. In an input orientation, one improves efficiency through proportional reduction of inputs, whereas an output orientation requires proportional augmentation of outputs. However, it is necessary to distinguish between a boundary point and an efficient boundary point. Moreover, the efficiency of a boundary point can be dependent upon the model orientation.

The efficient frontier and DEA projections are provided in Figures 2-1 and 2-2 for the input-oriented and output-oriented CCR models, respectively. In both cases, the efficient frontier obtained from the CCR model is the ray $\{\alpha\ (x_2, y_2) |\ \alpha \geq 0\}$ where x_2 and y_2 are the coordinates of P2.

Because of the points designated by the arrow head, an inefficient DMU may be projected to different points on the frontier under the two orientations. However, the following theorem provides a correspondence between solutions for the two models.

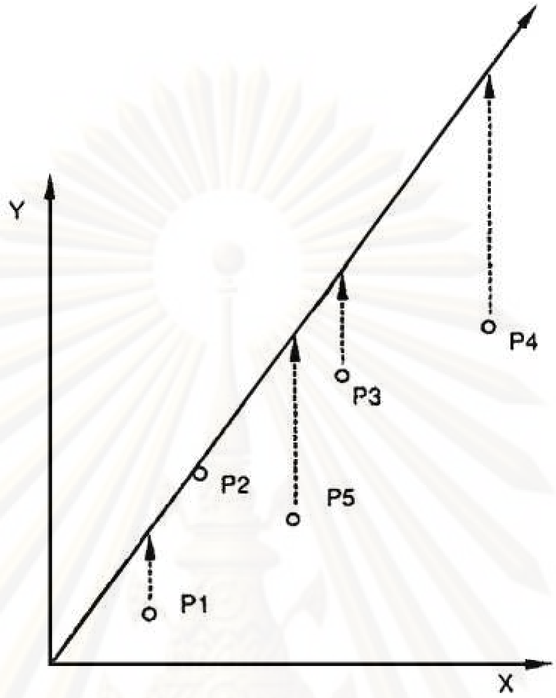
Theorem 1.1: Let (θ^*, λ^*) be an optimal solution for the input oriented model in (2.9). Then $(1/\theta^*, \lambda^*/\theta^*) = (\phi^*, \hat{\lambda}^*)$ is optimal for the corresponding output oriented model. Similarly if $(\phi^*, \hat{\lambda}^*)$ is optimal for the output oriented model then $(1/\phi^*, \hat{\lambda}^*/\phi^*) = (\theta^*, \lambda^*)$ is optimal for the input oriented model. The correspondence need not be 1-1, however, because of the possible presence of alternate optima (Cooper, Seiford, & Zhu, 2004: 15-17).

Figure 2-1 Projection to frontier for the input-orientated CCR model



SOURCE: Cooper, Seiford, & Zhu, (2004): 16

Figure 2-2 Projection to frontier for the output-orientated CCR model



SOURCE: Cooper, Seiford, & Zhu, (2004): 16

The *input-oriented* model is one version of a CCR model which aims to minimize inputs while satisfying at least the given output levels. Another model is the *output-oriented* model that attempts to maximize outputs without requiring more of any of the observed input values (Cooper, Seiford, & Tone, 2002: 41).

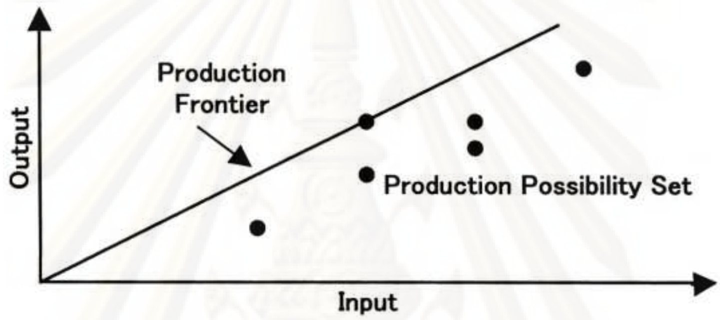
Input or output oriented?

One of the main purposes of a DEA study is to project the inefficient DMUs onto the production frontiers, e.g., the CCR-projection and the BCC projection, among others. There are three directions, one called *input-oriented* that aims at reducing the input amounts by as much as possible while keeping at least the present output levels, and the other, called *output-oriented,* maximizes output levels under at most the present input consumption. The third choice is represented by the Additive and SBM models (Slacks-Based Measure models) that deal with the input excesses and output shortfalls simultaneously in a way that maximizes both. If achievement of efficiency, or failure to do so, is the only topic of interest, then these different models will all yield the same result insofar as technical and mix inefficiency is concerned (Cooper, Seiford, & Tone, 2002: 103).

2.1.2 BCC DEA model

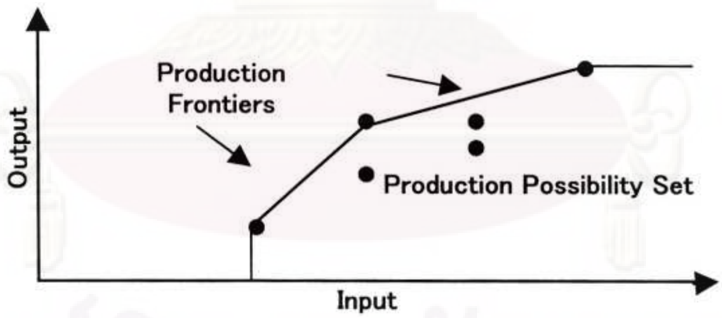
The CCR model is built on the assumption of *constant* returns to scale of activities. If an activity (x, y) is feasible, then, for every positive scalar t, the activity (tx, ty) is also feasible. Thus, the efficient production frontiers have constant returns-to-scale characteristics, as depicted Figure 2-3 for the single-input and single-output case. However, this assumption can be modified to allow extended types of production possibility sets with different postulates for the production possibility sets. In fact, various extensions of the CCR model have been proposed since the very beginning of DEA studies, among which the BCC (Banker-Charnes-Cooper) model is representative. The BCC model has its production frontiers spanned by the convex hull of the existing DMUs. The frontiers have piecewise linear and convex characteristics which, as shown in Figure 2-4, leads to *variable* returns-to-scale characterizations with (a) increasing returns-to-scale occurring in the first solid line segment followed by (b) decreasing returns-to-scale in the second segment and (c) constant returns-to-scale occurring at the point where the transition from the first to the second segment is made.

Figure 2-3 Production frontier of the CCR model



SOURCE: Cooper, Seiford, & Tone, (2002): 86

Figure 2-4 Production frontier of the BCC model



SOURCE: Cooper, Seiford, & Tone, (2002): 86

CCR-type models; under weak efficiency, evaluate the radial (proportional) efficiency θ^* but do not take account of the input excesses and output shortfalls. This is a drawback because θ^* does not include the nonzero slacks. Although the additive model deals with the input excesses and output shortfalls directly and can discriminate efficient and inefficient DMUs, it has no means to gauge the depth of inefficiency by a scalar measure similar to the θ^* in the CCR-type models (Cooper, Seiford, & Tone, 2002: 85-86).

2.1.3 Return to scale

RTS approaches with BCC models

Suppose that there are n DMUs (Decision Making Units) where every DMU_j, $j = 1, 2,..., n$, produces the same s outputs in (possibly) different amounts, y_{rj} (r = 1, 2, ..., s), using the same m inputs, x_{ij} (i = 1, 2,..., m), also in possibly different amounts. The efficiency of a specific DMU_o can be evaluated by the "BCC model" of DEA in "envelopment form" as follows,

$$\begin{aligned}
&\min \quad \theta_o - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\
&\text{subject to} \\
&\theta_o x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \qquad i = 1,2,\ldots,m; \\
&y_{ro} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \qquad r = 1,2,\ldots,s; \\
&1 = \sum_{j=1}^{n} \lambda_j \\
&0 \le \lambda_j, s_i^-, s_r^+ \qquad \forall\, i, r, j.
\end{aligned} \tag{2.11}$$

where, $\varepsilon > 0$ is a non-Archimedean element defined to be smaller than any positive real number.

The dual (multiplier) form of the BCC model represented in (2.11) is obtained from the same data which are then used in the following form,

$$\begin{aligned}
&\max \quad z = \sum_{r=1}^{s} u_r y_{ro} - u_o \\
&\text{subject to} \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_o \le 0 \qquad j = 1,\ldots,n \\
&\qquad\qquad \sum_{i=1}^{m} v_i x_{io} \qquad = 1 \\
&v_i \ge \varepsilon, \quad u_r \ge \varepsilon, \quad u_o \ \textit{free in sign}
\end{aligned} \tag{2.12}$$

The above formulations assume that x_{ij}, $y_{rj} \ge 0$ $\forall i,r,j$. All variables in (2.12) are also constrained to be non-negative – except for u_o which may be positive, negative or zero with consequences that make it possible to use optimal values of this variable to identify RTS.

When a DMU_o is efficient in accordance with the Definition 1.3, the optimal value of u_o, i.e., u_o^*, in (2.12), can be used to characterize the situation for Returns to Scale (RTS).

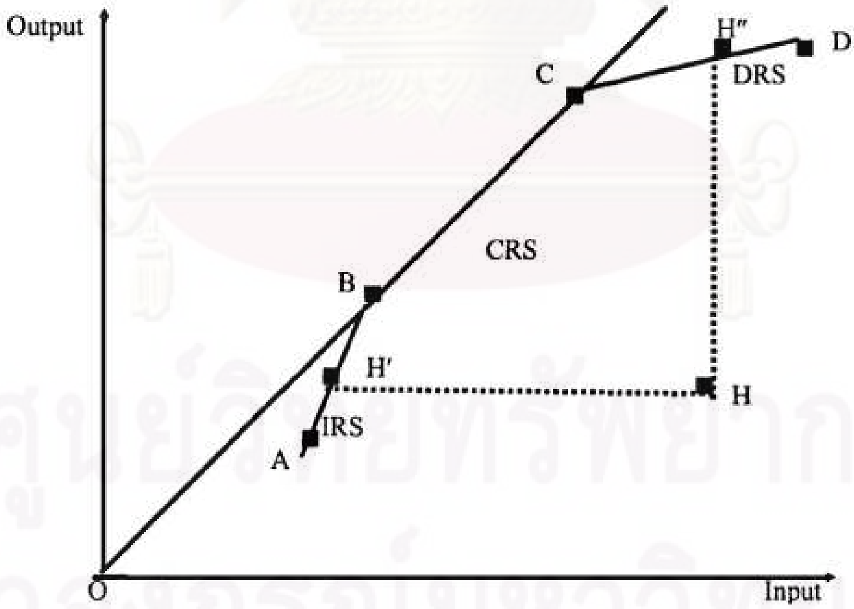
RTS generally has an unambiguous meaning only if DMU_o is on the efficiency frontier since it is only in this state that a tradeoff between inputs and outputs is required to improve one or the other of these elements. However, there is no need to be concerned about the efficiency status in the analyses because efficiency can always be achieved as follows. If a DMU_o is not BCC efficient, the optimal values can be used from (2.11) to project this DMU onto the BCC efficiency frontier via the following formulas,

$$\begin{cases} \hat{x}_{io} = \theta_o^* x_{io} - s_i^{-*} = \sum_{j=1}^{n} x_{ij}\lambda_j^*, & i = 1,\ldots,m \\ \hat{y}_{ro} = \quad y_{ro} + s_r^{+*} = \sum_{j=1}^{n} y_{rj}\lambda_j^*, & r = 1,\ldots,s \end{cases} \tag{2.13}$$

where the symbol "*" denotes an optimal value. These are sometimes referred to as the "CCR Projection Formulas" because Charnes, Cooper and Rhodes (1978) showed that the resulting $\hat{x}_{io} \geq x_{io}$ and $\hat{y}_{ro} \geq y_{ro}$ correspond to the coordinates of a point on the efficiency frontier. They are coordinates of the point used to evaluate DMU_o when (2.11) is employed.

Suppose there are five DMUs, A, B, C, D, and H as shown in Figure 2-5. Ray OBC is the constant returns to scale (CRS) frontier. AB, BC and CD constitute the BCC frontier, and exhibit increasing, constant and decreasing returns to scale, respectively. B and C exhibit CRS. On the line segment AB, increasing returns to scale (IRS) prevail to the left of B for the BCC model and on the line segment CD, decreasing (DRS) prevail to the right of C. By applying (2.13) to point H, there is a frontier point H' on the line segment AB of IRS. However, if the output-oriented BCC model is used, the projection is on to H" of DRS. This is due to the fact that the input-oriented and the output-oriented BCC models yield different projection points on the BCC frontier and it is on the frontier that returns to scale is determined.

Figure 2-5 Return to scale



NOTE: IRS = increasing RTS, CRS = constant RTS, DRS = decreasing RTS
SOURCE: Cooper, Seiford, & Zhu, (2004): 46

These present the theorem for returns to scale (RTS) as obtained from Banker and Thrall (1992) who identify RTS with the sign of u_o^* in (2.12) as follows:

Theorem 2.1
The following conditions identify the situation for RTS for the BCC model given in (2.12),

(i) Increasing RTS prevail at $(\hat{x}_o, \hat{y}_o)$ if and only if $u_o^* < 0$ for all optimal solutions.
(ii) Decreasing RTS prevail at $(\hat{x}_o, \hat{y}_o)$ if and only if $u_o^* > 0$ for all optimal solutions.
(iii) Constant RTS prevail at $(\hat{x}_o, \hat{y}_o)$ if and only if $u_o^* = 0$ for at least one optimal solution.

RTS approaches with CCR models

The CCR models take the following form,

$$\begin{aligned}
&\text{minimize } \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\
&\text{subject to} \\
&\theta x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \\
&y_{ro} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+, \\
&0 \le \lambda_j, s_i^-, s_r^+ \forall i, j, r.
\end{aligned} \tag{2.14}$$

This model is the same as the "envelopment form" of the BCC model in (2.11) except for the fact that the condition $\Sigma_{i=1}^{n}\ \lambda_j = 1$ is omitted. In consequence, the variable u_o appears in the "multiplier form" for the BCC model in (2.12), and it is omitted from the dual (multiplier) form of this CCR model. The projection formulas expressed in (2.13) are the same for both models. Therefore these same projections can be used to move all points onto the efficient frontier for (2.14) and proceed directly to returns to scale characterizations for (2.14) which are supplied by the following theorem from Banker and Thrall (1992).

Theorem 2.2
The following conditions identify the situation for RTS for the CCR model given in (2.14)

(i) Constant returns to scale prevail at $(\hat{x}_o, \hat{y}_o)$ if $\Sigma\ \lambda_j^* = 1$ in any alternate optimum.
(ii) Decreasing returns to scale prevail at $(\hat{x}_o, \hat{y}_o)$ if $\Sigma\ \lambda_j^* > 1$ for all alternate optima.
(iii) Increasing returns to scale prevail at $(\hat{x}_o, \hat{y}_o)$ if $\Sigma\ \lambda_j^* < 1$ for all alternate optima.

Following Banker, Chang and Cooper (1996), the need for examining all alternate optima can be avoided. Suppose an optimum has been obtained for (2.14) with $\Sigma\ \lambda_j^* < 1$, then replace (2.14) with

$$
\begin{aligned}
&\text{maximize } \sum_{j=1}^{n} \hat{\lambda}_j + \varepsilon\left(\sum_{i=1}^{m} \hat{s}_i^- + \sum_{r=1}^{s} \hat{s}_r^+\right) \\
&\text{subject to} \\
&\theta^* x_{io} = \sum_{j=1}^{n} x_{ij}\hat{\lambda}_j + \hat{s}_i^-, \quad \text{for i=1,…, m} \\
&\quad y_{ro} = \sum_{j=1}^{n} y_{rj}\hat{\lambda}_j - \hat{s}_r^+, \quad \text{for r=1,…, s} \\
&\quad\quad 1 \geq \sum_{j=1}^{n} \hat{\lambda}_j \\
&\text{with } 0 \leq \hat{\lambda}_j, \hat{s}_i^-, \hat{s}_r^+ \forall i, j, r,
\end{aligned}
\tag{2.15}
$$

where θ^* is the optimal value of θ secured from (2.5) (Cooper, Seiford, & Zhu, 2004: 43-49).

2.1.4 Allocative and overall efficiency

In situations that unit prices and unit costs are available. The concepts of “allocative” and “overall” efficiency are introduced and relate them to “technical efficiency” in a manner first introduced by M.J. Farrell (1957).

Figure 2-6 demonstrates the solid line segments connecting points ABCD constitute an “isoquant” or “level line’ that represents the different amounts of two inputs (x_1, x_2) which can be used to produce the same amount (usually one unit) of a given output. This line represents the “efficiency frontier” of the “production possibility set” because it is not possible to reduce the value of one of the inputs without increasing the other input if one is to stay on this isoquant.

The dashed line represents an isocost (=budget) line for which (x_1, x_2) pairs on this line yield the same total cost, when the unit costs are c_1 and c_2 respectively. When positioned on C the total cost is k. However, shifting this budget line upward in parallel fashion until it reaches a point of intersection with R would increase the cost to $k' > k$. In fact, k is the minimum total cost needed to produce the specified output since any parallel shift downward below C would yield a line that fails to intersect the production possibility set. Thus, the intersection at C gives an input pair (x_1, x_2) that minimizes the total cost of producing the specified output amount and the point C is therefore said to be “allocatively” as well as “technically” efficient.

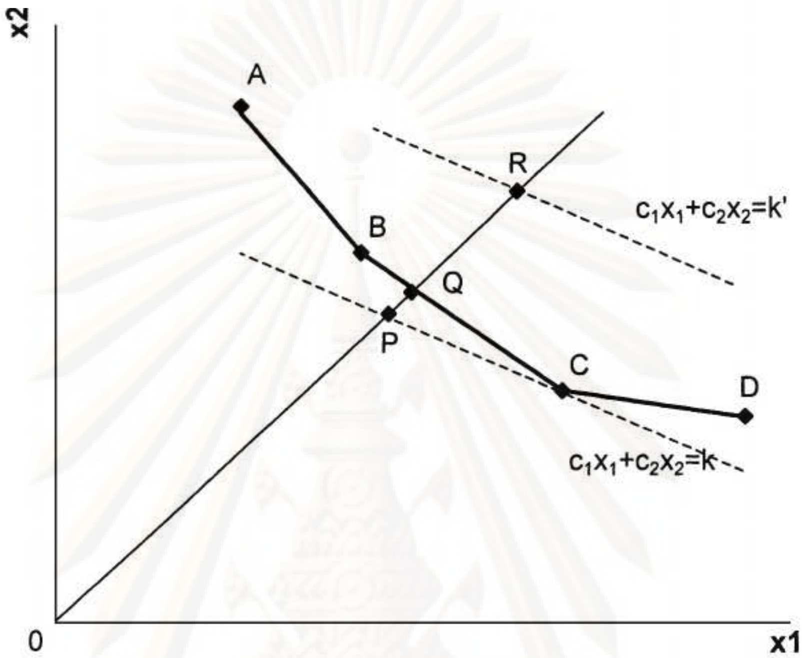
Let R represent an observation that produced this same output amount. The ratio $0 \leq OQ/OR \leq 1$ is said to provide a “radial” measure of technical efficiency, with $0 \leq 1 - (OQ/OR) \leq 1$ yielding a measure of technical inefficiency.

Now consider the point P which is at the intersection of this cost line through C with the ray from the origin to R. A radial measure of “overall efficiency” from the ratio $0 \leq OP/OR \leq 1$ can be obtained. In addition, the ratio $0 \leq OP/OR \leq 1$ obtains a measure of what Farrell (1957) referred to as “price efficiency” but is now more commonly called “allocative efficiency.” Finally, these three measures can be related to each other by noticing that

$$
\frac{OP}{OQ}\frac{OQ}{OR} = \frac{OP}{OR} \tag{2.16}
$$

which can be verbalized by saying that the product of allocative and technical efficiency equals overall efficiency in these radial measures (Cooper, Seiford, & Zhu, 2004: 27-28).

Figure 2-6 Allocative and overall efficiency



SOURCE: Cooper, Seiford, & Zhu, (2004): 28

Decomposition of technical efficiency

The objective is to investigate the sources of inefficiency that a DMU might have. Is it caused by the inefficient operation of the DMU itself or by the disadvantageous conditions under which the DMU is operating?

The comparisons of the (input-oriented) CCR and BCC scores deserve considerations. The CCR model assumes the constant returns-to-scale production possibility set, i.e., it is postulated that the radial expansion and reduction of all observed DMUs and their non-negative combinations are possible hence the CCR score is called *global technical* efficiency. On the other hand, the BCC model assumes the convex combinations of the observed DMUs as the production possibility set and the BCC score is called *local pure technical* efficiency. If a DMU is fully efficient (100%) in both the CCR and BCC scores, it is operating in the *most productive scale size.* If a DMU has the full BCC efficiency but a low CCR score, so it is operating locally efficient but not globally efficient due to the scale size of the DMU. Thus, it is reasonable to characterize the *scale efficiency* of a DMU by the ratio of the two scores (Cooper, Seiford, & Tone, 2002: 136). This includes treatments with the BCC (Banker, Charnes and Cooper) and CCR (Charnes, Cooper and Rhodes) models as well as the ‘‘additive’’ and ‘multiplicative’’ models (Cooper, Seiford, Thanassoulis, & Zanakis, 2004).

2.1.5 Scale efficiency

Based on the CCR and BCC scores, *scale efficiency* is defined as follows:

Definition 1.6 (Scale Efficiency) *Let the CCR and BCC scores of a DMU be* θ^*_{CCR} *and* θ^*_{BCC} *respectively. The scale efficiency is defined by*

$$SE = \frac{\theta^*_{CCR}}{\theta^*_{BCC}}. \qquad (2.17)$$

SE is not greater than one. For a BCC-efficient DMU with CRS characteristics, i.e., in the most productive scale size, its scale efficiency is one. The CCR score is called the (global) *technical* efficiency (TE), because it takes no account of scale effect. On the other hand, the BCC expresses the (local) *pure technical* efficiency (PTE) under variable returns-to-scale circumstances. Using these concepts, relationship (2.17) demonstrates a decomposition of efficiency as:

[Technical Eff. (TE)] = [Pure Technical Eff. (PTE)] × [Scale Eff. (SE)] (2.18)

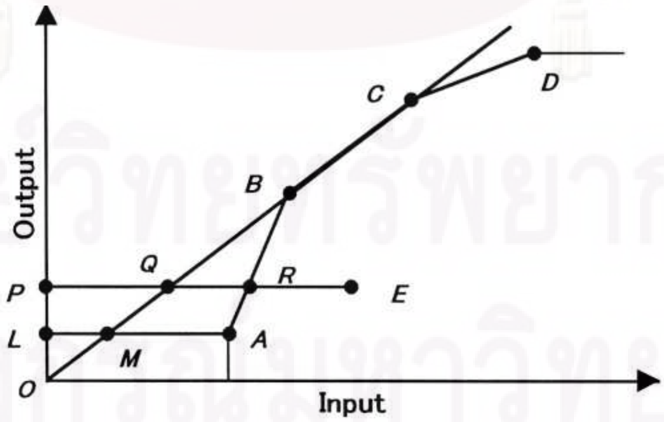
This decomposition is unique and it depicts the sources of inefficiency, i.e., whether it is caused by inefficient operation (PTE) or by disadvantageous conditions displayed by the scale efficiency (SE) or by both.

In single input and single output case, the scale efficiency can be illustrated by Figure 2.7. For the BCC-efficient *A* with IRS, its scale efficiency is given by

$$\mathrm{SE}(A) = \theta^*_{CCR}(A) = \frac{LM}{LA} < 1,$$

which denotes that *A* is operating locally efficient (PTE=1) and its overall inefficiency (TE) is caused by the scale inefficiency (SE) expressed by *LM/LA.*

Figure 2-7 Scale efficiency



SOURCE: Cooper, Seiford, & Tone, (2002): 137

For DMUs *B* and *C*, their scale efficiencies are one, i.e., they are operating at the most productive scale size. For the BCC-inefficient DMU *E,* there are

$$\mathrm{SE(E)} = \frac{PQ}{PE}\frac{PE}{PR} = \frac{PQ}{PR},$$

which is equal to the scale efficiency of the input-oriented BCC projection *R*.
The decomposition of *E* is

$$\mathrm{TE(E)} = \mathrm{PTE(E)} \times \mathrm{SE(E)}$$

$$\frac{PQ}{PE} = \frac{PE}{PR}\frac{PQ}{PR}.$$

So, *E's* overall inefficiency is caused by the inefficient operation of *E* and at the same time by the disadvantageous conditions of *E*.

Although the above scale efficiency is input-oriented, the *output-oriented scale efficiency* can be defined using the output-oriented scores, as well (Cooper, Seiford, & Tone, 2002: 136-138).

2.1.6 Analyzing DEA scores with censored regression models

DEA's greatest potential contribution to health care helps managers, researchers, and policy makers understand why some providers perform better or worse than others do. There are many variations in performance such as: (1) the characteristics of the patients, (2) the practice styles of physicians, (3) the micro-processes of care, (4) the managerial practices of the delivery systems, or (4) other factors in the environment. The following general model has been used in this type of health care study:

> DEA score = f (ownership, competitive pressure, regulatory pressure, demand patterns, wage rates, patient characteristics, physician or provider practice characteristics, organizational setting, managerial practices, patient illness characteristics, and other control variables).

The DEA scores depend on the selection of inputs and outputs. Hence every health application is obliged to disconfirm the hypothesis that DEA is not measuring efficiency, but is actually picking up the differences in case mix or other non-discretionary variables. The best way to validate or confirm variations in DEA scores is to regress the DEA scores against explanatory and control variables. But what type of regression models should be used?

If DEA scores are used in a two-stage regression analysis to explain efficiency, a model other than ordinary least square (OLS) is required. Standard multiple regression assumes the normal and homoscedastic distribution of the disturbance and the dependent variable; however, in the case of a limited dependent variable, the expected errors will not equal zero. Hence, standard regression will lead to a biased estimate. Logit models can be used if the DEA scores are converted to a binary variable such as efficient/inefficient. However, the converting of scores < 1 to a categorical variable results in the loss of valuable information; consequently logit is not recommended as a technique for exploring health care problems with DEA.

Tobit model can also be used whenever there is a mass of observations at a limiting value. This works very well with DEA scores which contain both a limiting value (health care providers: whose DEA scores are clustered at 1) and some continuous parts (health care providers: whose DEA scores fall into a wide variation of strictly positive values < 1). No information is lost and a tobit model fits nicely with distribution of DEA scores as long as there are enough best practice providers. For example, if in a sample of 200 providers less than 5 were on the frontier, a tobit model would not be suitable.

In the econometrics literature, it is customary to refer to a distribution of DEA as either a truncated or a censored normal distribution. There is a basic distinction to be made between truncated and censored regressions. Truncation occurs when there are no observations for either the dependent variable; y, or the explanatory variables; x. In contrast, a censored regression model has data on the explanatory variables; x, for all observations but the values of the dependent variable are above (or below) a threshold and they are measured by a concentration of observations at a single value. The concentration of threshold values is often based on an actual measure of the dependent variable – i.e., zero arrests, zero expenditures – rather than an arbitrary value based on a lack of information.

DEA analysis does not exclude observations greater than 1; rather the analysis simply does not allow a DMU to be assigned a value greater than 1. Hence, Chilingerian (1995) has argued that DEA scores are best conceptualized as a censored, rather than a truncated distribution. The censored model would take the following form:

Efficiency score = actual score if score < 1
Efficiency score = 1 otherwise

A censored tobit model fits a line which allows for the possibility of hypothetical scores > 1. The output can be interpreted as "adjusted" efficiency scores based on a set of explanatory variables strongly associated with efficiency. To understand why censored regression models make sense here, one must consider how DEA evaluates relative efficiency.

DEA scores reflect relative efficiency within similar peer groups without reference to relative efficiency among peer groups. For example, an efficient provider scoring 1 in a peer group using a different mix of inputs may produce more costly care than a provider scoring 1 in a peer group using another mix of inputs. Superior efficiency may not be reflected in the DEA scores because the constraints in the model do not allow a decision making unit to be assigned a value greater than 1. If DEA scores could be re-adjusted to compare efficiencies among peer groups, some physicians could have a score that is likely to be greater than 1. Despite the advantages to blending nonparametric DEA with censored regression models in practice, some conceptual problems do arise.

The main difficulty of using tobit to regress efficiency scores is that DEA does not exactly fit the theory of a censored distribution. The theory of a censored distribution argues that due to an underlying stochastic choice mechanism or due to a defect in the sample data there are values above (or below) a threshold that are not observed for some observations. As mentioned above, DEA does not produce a concentration of ones due to a defect in the sample data; rather it is embedded in the mathematical formulation of the model.

A second difficulty of using tobit is that it opens up the possibility of rank ordering superior efficiency among physicians on the frontier; in other words, “hypothetical” scores > 1. In production economics, the idea that some DMUs with DEA scores of 1 may possibly have scores > 1 makes no sense. It suggests that some candidates for technical efficiency (perhaps due to random shifts such as luck, or measurement error) are actually less efficient.

Despite these drawbacks, blending DEA with tobit model’s estimates can be informative. Although DEA does not fit the theory of a censored regression, it easily fits the tobit model and makes use of the properties of a censored regression in practice. For example, the output can be used to adjust efficiency scores based on factors strongly associated with efficiency.

Tobit may have the potential to sharpen a DEA analysis when expert information on input prices or exemplary DMUs is not available. So in a complex area like physician utilization behavior, tobit could help researchers to understand the need to introduce boundary conditions for the DEA model’s virtual multipliers.

The distribution of DEA scores is never normally distributed, and often skewed. Taking the reciprocal of the efficiency scalar; (1/DEA score), helps to normalize the DEA distribution.

Greene (1993) points out that for computational reasons; a convenient normalization in tobit studies is to assume a censoring point at zero. To put a health care application into this form, the DEA scores can be transformed with the formula:

$$\text{Inefficiency score} = (1/\text{DEA score}) - 1$$

Thus, the DEA score can become a dependent variable that takes the following form:

$$\text{DEA Inefficiency score} = \text{x } B + u \text{ if efficiency score} > 0$$
$$\text{DEA Inefficiency Score} = 0 \text{ otherwise}$$

When health care providers’ DEA scores have been transformed, tobit becomes a very convenient and easy method to use for estimating efficiency. The slope coefficients of tobit are interpreted as if they were an ordinary least squares regression. They represent the change in the dependent variable with respect to a one unit change in the independent variable, holding all else constant.

When using tobit models they can tested with a log-likelihood ratio test. This statistic is calculated by -2 log(λ), where log(λ) is the difference between the log of the maximized value of the likelihood function with all independent variables equal to zero, and the log of the maximized values of the likelihood function with the independent variables as observed in the regression. The log-likelihood ratio test has a chi square distribution where the degrees of freedom are the number of explanatory variables in the regression (Cooper, Seiford, & Zhu, 2004: 513-517).

2.2 Concept of hospital efficiency measurement

There are many categories of efficiency such as technical, scale, allocative, and overall efficiency. Most studies in health care have measured the overall technical and scale components of clinical efficiency.

Researchers can use a variety of DEA models to measure and explain overall technical and scale efficiency. The CCR model, initially proposed by Charnes, Cooper and Rhodes (1978) is considered a sensitive model for finding inefficiencies. In 1984, Banker et al. added another very useful model (BCC model) for health care studies. The BCC model can be used to separate technical from scale efficiency. Both models (if formulated as input-minimizing) can be used to explore some of the underlying reasons for inefficiency; for example, to estimate divergence from most productive scale size and returns to scale. Consequently, DEA can yield theoretical insights about the managerial problems or decision choices that underlie the efficient relationships such as magnitude of slack, scale effects of certain outputs on the productivity of inputs, marginal rates of substitution and marginal rates of transformation and so on.

When DEA rates a group of providers efficient and inefficient, the researchers, managers and/or policy makers can use this information to benchmark best practice by constructing a theoretical production possibility set. Analysts or researchers could use the DEA linear programming formulations to estimate potential input savings (based on a proportional reduction of inputs). They can use the ratios of the weights and to provide estimates of marginal rates of substitution and marginal rates of transformation of outputs, measured on a segment of the efficient frontier. Again, they could use the BCC model to evaluate returns to scale such as in the case of physicians, the effects of a small versus large proportion of high severity cases (Cooper, Seiford, & Zhu, 2004: 493-494).

Depending on the type of health care organization, there are many ways of conceptualizing the inputs and outputs of production. Since the selection of inputs and outputs often drives the DEA results, it is important to develop a justification for selecting inputs and outputs.

Managerial and Clinical Efficiency Models

In health care, technical efficiency is not always synonymous with managerial efficiency. Technical efficiency in nursing homes, rehabilitation hospitals, and mental health facilities can be equated with managerial efficiency. However, medical care services especially in acute hospitals and primary care settings are fundamentally different in that there are two medical care production processes, and consequently types of technical and scale efficiency: managerial and clinical efficiencies. Managerial efficiency requires practice management; for example, achieving a maximum output from the resources allocated to each service department, given clinical technologies. Clinical efficiency requires patient management; for example, physician decision making that utilizes a minimal quantity of clinical resources to achieve a constant quality outcome, when caring for patients with similar diagnostic complexity and severity (Cooper, Seiford, & Zhu, 2004: 493-494). Although mixing managerial inputs with clinical outputs is acceptable, the managerial and clinical inefficiencies become indistinguishable (Cooper, Seiford, & Zhu, 2004: 498).

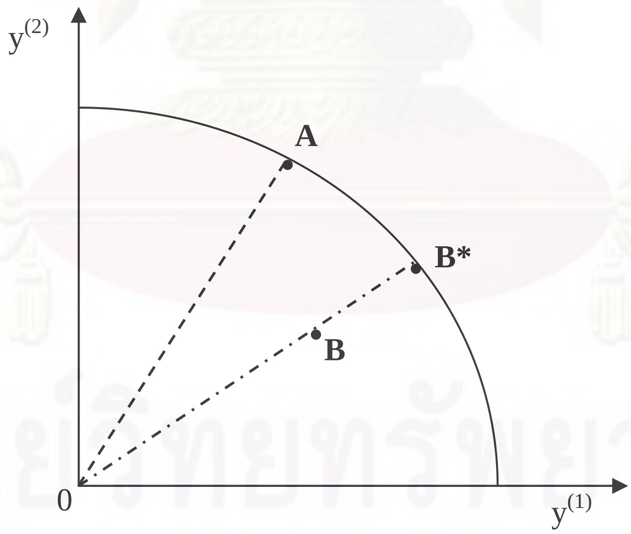
The technical efficiency refers to the use of productive resources in the most technologically efficient manner or the maximal possible outputs from a given set of inputs or; in reverse, minimum possible inputs from a given set of outputs.

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

Efficiency measurement in 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. Input-oriented measurement assumes that the firm can change quantities of inputs, while quantities of outputs are fixed, to meet the most efficient point. In the reverse, output-orientated measurement assumes that quantities of outputs can change to match with the most efficiency point while quantities of inputs are fixed. These concepts can apply to measure technical efficiency of hospitals or relatively compare hospital efficiency in set of interesting groups. The most efficient hospitals are on the frontier line and are the best practice hospitals in that set (Kornpob Bhirombhakdi, 2008).

The Figure 2-8 graphically represents a production frontier with a given production process of firms and inputs. Firms A and B are plotted in the output space. In this graph, firm A is on the frontier and firm B is not. Firm A can not expand its production level, but firm B can expand its production level to point B* (Yoshikawa, 1996).

Figure 2-8 Production frontier and technical efficiency measurement



SOURCE: Yoshikawa, (1996): 146

Technical efficiency (TE) or Technical efficiency under constant return to scale assumption (TECRS) consists of:

1) "Pure" technical efficiency or Technical efficiency under variable return to scale assumption (TEVRS)
2) Scale efficiency (SE)

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

(1) Increasing return to scale (IRS)
(2) Constant return to scale (CRS) and
(3) Decreasing return to scale (DRS) (Kornpob Bhirombhakdi, 2008).

2.3 Previous studies on hospital efficiency

The two most commonly used approaches of hospital efficiency measurement are data envelopment analysis (DEA) and stochastic frontier analysis (SFA). Both are similar in that efficiency is measured relative to a best practice (or efficient) frontier. Deviations from this frontier (usually measured as a geometric distance) give measures of (relative) efficiency (Rajitkanok A. Puenpatom & Rosenman, 2008).

Data envelopment analysis (DEA) and stochastic frontier analysis (SFA)

Data envelopment analysis (DEA) and stochastic frontier regression (SFR) models compared the results of scoring hospital efficiency of acute care hospitals in Florida over the period 1982-1993. The results revealed DEA and SFR models yielded convergent evidence about hospital efficiency at the industry level, but divergent portraits of the individual characteristics of the most and least efficient facilities. Hospital policymakers should not be indifferent to the choice of the frontier model used to score efficiency relationships. They may be well advised to wait until additional research clarifies reasons why DEA and SFR models yield divergent results before they introduce these methods into the policy process (Chirikos & Sear, 2000).

This study used the same dataset from the UK Department of Health and compared the efficiency rankings from the cost indices using data envelopment analysis (DEA) and stochastic frontier analysis (SFA). The results found that each method had particular strengths and weaknesses and potentially measured different aspects of efficiency. Several specifications should be used to develop ranges of inefficiency to act as signaling devices rather than point estimates. The differences in efficiency scores across different methods might be due to random “noise” and reflect data deficiencies. The conclusion concurred with previous findings that there were not truly large efficiency differences between NHS hospitals (Trusts) and savings from bringing up poorer performers would in fact be quite modest (Jacobs, 2001).

Funding in Irish hospitals was partially based on case mix, whereby resources were redistributed annually to hospitals with greater efficiency. Accurate measurement of efficiency was essential, so in this study, Data Envelopment Analysis and Stochastic Frontier Analysis were used to measure technical efficiency of acute public hospitals in Ireland between 1995 and 2000. The results provided estimates of average technical efficiency in the hospital sector in Ireland for the first time, and highlighted the variation in technical efficiency levels across hospitals (Gannon, 2005).

This study is interesting in DEA model which is the most popular technique which uses the concept of linear programming to evaluate the efficiency score by construction of a non-parametric frontier, over the data to calculate efficiencies relative to this surface. DEA model has the strengths and limitations.

Strengths of DEA

DEA can be a useful tool. A few of the characteristics that make it powerful are:

- DEA can handle multiple inputs and multiple outputs.
- It does not require an assumption of a functional form relating inputs to outputs.
- DMUs are directly compared against a peer or combination of peers.
- Inputs and outputs can have very different units; for example, beds, number of medical staff, number of patients treated, and expenditure on medical supplies, etc.

Limitations of DEA

The same characteristics that make DEA a useful tool can also create the problems. An analyst should keep these limitations in mind when deciding whether or not to use DEA.

- DEA results are sampled specific.
- Since DEA is an extreme point technique, measurement error can cause significant problems.
- DEA is good at estimating ‘relative’ efficiency of a DMU but it converges very slowly to ‘absolute’ efficiency. In other words, it can tell you how well you are doing compared to your peers but not compared to a ‘theoretical maximum’.
- Since DEA is a non-parametric technique, statistical hypothesis tests are difficult.
- Since a standard formulation of DEA creates a separate linear programme for each DMU, large problems can be computationally intensive (Bhat, Verma, & Reuben, 2001: 320-321).

There are 2 main types of services of large hospitals like regional hospitals.

1) **Health care service**

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

The study reviewed the Data Envelopment Analysis (DEA), a technique particularly appropriated when multiple outputs were produced from multiple inputs and measured the productive performance of health care services, since the mid-1980s. This paper particularly reviewed the concept and measurement of efficiency and productivity. Applications to hospitals and to the wider context of general health care were reviewed and the empirical evidence from both the USA and Europe (EU) were that public rather than private provision was more efficient (Hollingsworth, Dawson, & Maniadakis, 1999).

The study used a two-stage procedure to assess the impact of actual DRG payment on the productivity (through its components; i.e., technological change and technical efficiency change) of diagnostic technology in Portuguese hospitals during the year 1992-1994 using parametric and non-parametric frontier models. The results found that the DRG payment system appeared to have had a positive impact on productivity and technical efficiency of some commonly employed diagnostic technologies in Portugal during this time span (Dismuke & Cena, 1999).

In national health services, where there was a tendency towards a lack of resources and a continuous increased in demand, it was necessary to implement decisions that promoted efficiency. This study focused on potential diversification economies as a strategy to increase efficiency levels. Data envelopment analysis was used to evaluate the change in efficiency in Catalan hospitals between 1987 and 1992; in addition, analyze the presence of possible diversification economies in each hospital. The results found that the majority of hospitals could increase their efficiency and reduce their costs by diversification to the output-mix offered. Potential productivity gains were between 29% and 46% (Prior & Sola`, 2000).

Data envelopment analysis was used to examine public sector hospital efficiency in 80 provincial markets in Turkey. Outputs of the study included mortality rate as quality measure as well as inpatient discharges and outpatient visits. Patient beds, four levels of health labor, and expenditures were used to capture capital, labor and material resources as inputs. The results found that 55% of the public hospitals in served markets were operated inefficiently. Analysis of inefficient provinces suggested that in those 44 inefficient provinces were collectively over-bedded; employ excessive number of specialists and other health labor. They spent approximately $70,000,000 from their revolving funds in excess compared to efficient provinces (Sahin & Ozcan, 2000).

To investigate the evolution of efficiency and productivity in the hospital sector of an Austrian province for the time period 1994–1996, the data envelopment analysis (DEA) was used to measure technical efficiency scores employing the number of case mix-adjusted discharges and of inpatient days, in a second used credit points, which were calculated in course of the newly introduced diagnosis related group-type financing system. In second approach compared individual efficiency scores for hospital wards (total 31 wards) as decision making units (DMU) in specified medical fields. The results found that from model 1 with conservative output measurement calculated an average efficiency level of 96%, and model 2 with credit points for output measurement got average efficiency at 70% (Hofmarcher, Paterson, & Riedel, 2002).

In Sub-Saharan Africa (SSA), there was a huge knowledge gap of health facilities performance. Data envelopment analysis (DEA) technique was used to measure relative technical efficiencies of 54 public hospitals in Kenya. The results found 14 (26%) of public hospitals were technically inefficient. The study singled out the inefficient hospitals and provided the magnitudes of specific input reductions or output increases needed to attain technical efficiency (Kirigia, Emrouznejad, & Sambo, 2002).

The non-parametric, output-orientated data envelopment analysis was used to document empirical evidence on the relationship between hospital ownership and operating efficiency using annual cross-sectional data on Taiwan hospitals over the period 1996–1997. Hospitals within the same category were compared on the basis of their relative efficiency. Conventional and data-envelopment-analysis-based test procedures were employed to test for efficiency differences between public and private hospitals. The statistical test results indicated that, in general, public hospitals were less efficient than private hospitals for both regional and district hospitals. Specifically, the study provided evidence that private hospitals without intensive-care units outperform their public counterparts (Chang, Cheng, & Das, 2004).

Input-oriented, data envelopment analysis (DEA) methodology was used to evaluate the technical efficiency of federal hospitals in the United States using a variable returns to scale. Hospital executives, health care policy-makers, taxpayers, and other stakeholders, benefited from studies that improved the efficiency of federal hospitals. Data for 280 federal hospitals in 1998 and 245 in 2001 were analyzed using DEA to measure hospital efficiency. The results indicated overall efficiency in federal hospitals improved from 68% in 1998 to 79% in 2001. However, based upon 2001 spending of $42.5 billion for federal hospitals potential savings of $2.0 billion annually were possible through more efficient management of resources. From a policy perspective, this study highlighted the importance of establishing more specific policies to address inefficiency in the federal health care industry (Harrison, Coppola, & Wakefield, 2004).

Data Envelopment Analysis was used to computed the hospital efficiency scores of 53 Virginia hospitals performance measures of quality were examined related to technical efficiency. The study revealed that the technically efficient hospitals were performing well as far as quality measures were concerned. Some of the technically inefficient hospitals were performing well with respect to quality. DEA can be used to benchmark both dimensions of hospital performance: technical efficiency and quality. The results had policy implications in view of growing concern that hospitals may be improving their efficiency at the expense of quality (Nayar & Ozcan, 2008).

DEA was used to compute efficiency scores and Malmquist indexes for a panel data set comprising 68 Portuguese public hospitals belonging to the National Health System (NHS) in the period 2000-2005, when several units started being of an entrepreneurial framework. With data on hospital services' and resource quantities, an output distance function was constructed, and assessed by how much can output quantities be proportionally expanded without changing input quantities. The results show that; on average, the NHS hospital sector revealed positive but small productivity growth between 2000 and 2004. The mean TFP indices varied between 0.917 and 1.109, implying some differences in the Malmquist indices across specifications. Furthermore, there were significant fluctuations among NHS hospitals in terms of individual efficiency scores from one year to the other (Afonso & Fernandes, 2008).

The objective of the study was to explain the relationship between the case-mix specialization index and efficiency of inpatient hospital care services and hospital specialization using the information theory index constructed from diagnosis-related group numbers of hospitals in Seoul, Korea, in 2004. The data envelopment analysis to measure technical efficiency scores and multiple regression analysis models were applied to identify the internal and external factors that affected the extent of hospital specialization status as well as the efficiency of hospitals. The results showed input variables such as the number of beds, doctors and nurses were related to hospital efficiency and hospitals had different levels of specialization in patient services, and more specialized hospitals were more likely to be efficient (odds ratio = 25.95). In addition, internal characteristics of providers had more significant effects on the extent of specialization than market conditions (Lee, Chun, & Lee, 2008).

2) Medical education services

Data envelopment (DEA) type approach was used to compare the frontiers of 236 teaching hospitals and 556 non-teaching hospitals in the US in 1994 in term of their provision of patient services. The results found that only 10% teaching hospitals could effectively complete with non-teaching hospitals based on the provision of patient services (Grosskopf, Margaritis, & Valdmanis, 2001a).

In addition to providing direct patient care, some hospitals were also used as training sources for residents. Because of these additional responsibilities, total costs were typically higher in teaching hospitals than in their non-teaching counterparts. Data envelopment analysis (DEA) methodology was used to assess the relative technical efficiency of the 213 teaching hospitals in the sample including only those hospitals that had non-zero values for all outputs, inputs, and trained full time equivalent medical residents/interns. DEA was able to specify multiple inputs and outputs in determining the 'best practice frontier' and determined the excess resources employed by technically inefficient hospitals. Expanding the use of a DEA, this study was also able to determine how much of the inefficiency was due to excess use of residents, i.e., 'congestion'. Systematic differences in terms of hospital ownership, teaching dedication, and teaching intensity were included in the analysis. The result found an average inefficiency score of 0.80, indicating that these hospitals could have reduced inputs by 20% while maintaining output levels. Inefficiency attributed to the congestion of residents amounted to 20% of the total inefficiency score (Grosskopf, Margaritis, & Valdmanis, 2001b).

Data envelopment analysis (DEA) approach was used to measure the relative technical and scale efficiencies of 254 US teaching hospitals and assessed in a bivariate context the effect market competition had on the teaching hospitals. This study evaluated the performance of US teaching hospitals operating in 1995. Since teaching hospitals must increasingly compete with non-teaching hospitals for managed care contracts based on price, decreasing costs could only come from either reducing inefficiencies or decreasing the ‘public good’ production of teaching and research. The result found that competition (as measured by the number of managed care contracts per hospital and the number of patients covered by these contracts per hospital) had positive effects on the teaching hospitals. In other words, as competition increased so did the teaching hospitals relative efficiency. The study also regressed each hospital’s relative efficiency scores on ownership form, organization structure, teaching effort, and competitive market variables. The results revealed that increased competition leaded to higher efficiency without compromising teaching intensity (Grosskopf, Margaritis, & Valdmanis, 2004).

The data envelopment analysis (DEA) was used to assess the association between hospital ownership and technical efficiency in a managed care environment employing four input variables and three output variables from the American Hospital Association Hospital Survey Data for acute care general hospitals in Florida. By utilizing the hospital technical efficiency scores as a dependent variable, non-profit hospitals were more efficient than for-profit hospitals in 2001-2004 and teaching hospitals were more efficient than non-teaching hospitals in 2001-2003, but not in 2004 (Lee, Yang, & Choi, 2009).

2.4 Previous studies on hospital efficiency in Thailand

The study of the level of technical efficiency of 662 public community hospitals in Thailand used the fixed-effects model approach since 1996-2000. The input variables used were capital expenses, labor expenses and material/ supplies expenses and the output variables included outpatient visits, inpatient days and accident emergency cases. The results of study showed average efficiency score was 0.55 and there was a wide variation of technical efficiency scores; in addition, larger size hospitals tended to be efficient than smaller hospitals. The determinants of technical efficiency were tested by multiple regression model and the significant determinants were classified as the internal factors; included age of hospital, size of hospital, and management of human resources and the external factors; included community demographic situation and competitive environment (Pirudee Pavananunt, 2004).

The data envelopment analysis (DEA) was used to assess the capacity of 68 Thai public hospitals (regional, large general and smaller general hospitals) in 1999 to proportionately expand service to both the poor and the non-poor. Seven inputs were the number of beds, doctors, nurses, other staff, allowance expenditures, drug expenditures, and other operating expenditures. Four outputs were number of outpatient visits for poor patients, number of outpatient visits for nonpoor patients, total inpatient cases adjusted with average diagnostic related group (DRG) weighting for poor patients and total inpatient cases adjusted with average diagnostic related group (DRG) weighting for nonpoor patients. The study found that increases in the amount of services provided to poor patients did not reduce the amount of services to nonpoor patients and overall hospitals were producing services relatively closed to their capacity given fixed inputs (Valdmanis, Kumanarayake, & Jongkol Lertiendumrong, 2004).

The data envelopment analysis (DEA) model was use to assess technical efficiency index of 72 provincial hospitals in Thailand in 2002 and the study focused on two major inputs; health personnel and hospital beds, and three outputs; morbidity of top-ten causes, infant and maternal mortality to determine the effects of customer/ patient types on the efficiency or inefficiency of the hospital system as different patient types meant different pressure on cost containment. A technical efficiency index function as structure of hospital patients was analyzed using truncated normal distribution. The results showed there was no significant evidence that the new health security policy causes technical inefficiency of the government hospitals but there were the significant marginal effects of social welfare scheme and government employee health benefit on the hospital technical efficiency (Pongsa Pornchaiwiseskul, 2005).

Data envelopment analysis (DEA) was employed to study 166 medium size-community hospitals (between 31-60 beds) under the Ministry of Public Health in Thailand about the relative efficiency of hospital cost management, based on cost- and performance statistics of hospitals for the fiscal year 2005. Input variables were personnel costs and operating expenses and output variables were inpatient-day, out patient service provided, and the number transferred patient (received cases). The results found the average efficiency was 78% and 17 hospitals were on the cost-frontier based on the variable returns to scale (VRS) assumption. The researcher suggested investigating in-depth or qualitative study from hospital manager to deepen understanding the real situations (Direk Patmasiriwat, 2007).

All 805 public hospitals (including small community, large community, small general, large general and regional hospitals) in Thailand in year 2001 and 2006 were studied by usage of the data envelopment analysis to measure technical efficiency scores. The results found that only 35 (4.3%) are technically efficient hospitals that were located on the frontier and the average pure technical efficiency score of all public hospitals is 67.3%. The large hospitals are more efficient than small ones and the minimum pure technical efficiency score of regional hospital is 66.3%. The average scale efficiency score of all public hospitals is 88.6% and most hospitals are operating very close to their optimal size. The pattern of scale inefficiency showed that decreasing returns to scale were among in regional and general hospitals while about 96.2% of small community hospitals were operating on increasing return to scale. For cost efficiency analysis, regional and general hospitals are more cost and technical efficient than community hospitals. All levels of public hospitals were allocatively efficient at efficiency score more than 90%. The results of Tobit regression showed that the numbers of bed, occupancy rate, geographic location and service complexity were associated with technical efficiency (Watchai Charunwatthana, 2007).

5 university hospitals in Thailand were measured the hospital efficiency of public hospitals by data envelopment analysis (DEA) and identified the determinants of the efficiency by regression analysis. 29 data from since 2001 to 2007 were analyzed; the inputs of DEA used the number of bed and number of physician, and outputs were OPD visits, IPD bed days and number of medical student year 6^{th}. The result found that efficiency scores were ranged from 0.525 to 1, average was about 0.887 and 72.4% of decision making units (DMUs) were found inefficiency in scale, while about 31.0% were inefficiency in technique. Among the scale inefficiency

hospitals, most of them (95.2%) were operated with decreasing returns to scale pattern. The results of regression analysis showed that bed-physician ratio and pharmacist-physician ratio related to scale efficiency score significantly. For technical efficiency score was significantly related to occupancy rate, out-patient visit-physician ratio and number of medical student year 6th-bed ratio. This study shows most university hospitals were running in a decreasing return to scale pattern; for policy makers, downsizing of the hospitals should be done to meet the most efficiency scale at constant return to scale pattern. Utilization at the maximal capacity of bed or decreasing number of bed should be one solution to be considered because from the study shows that bed-physician ratio and occupancy rate highly significantly related to technical efficiency score (Kornpob Bhirombhakdi, 2008).

Data envelopment analysis was used to investigate the impact of implementing capitated-based Universal Health Coverage (UC) in Thailand on technical efficiency in larger public hospitals during the policy transition period. The study measured the efficiency 92 regional and general public hospitals; outside of Bangkok, before and during the transition period of UC using a two-stage analysis with Data Envelopment Analysis, bootstrap DEA, and truncated regressions. General hospitals consisted of 200 to 500 beds, while regional hospitals had over 500 beds. The analysis indicated that during the transition period efficiency in larger public hospitals across the country increased. The findings differed by region, and hospitals in provinces with more wealth not only started with greater efficiency, but also improved their relative position during the transitional phases of the UC system (Rajitkanok A. Puenpatom & Rosenman, 2008).

CHAPTER III

RESEARCH METHODOLOGY

3.1 Study design

This is a descriptive study employing econometric techniques for its analysis. A cross section model with most secondary panel data and one primary panel data from the year 2007-2008 was used for data envelopment analysis (DEA) and regression analysis using ordinary least squares (OLS).

3.2 Target and study population

The target population included all public regional hospitals in Thailand. There were twenty-five regional hospitals in the year 2007-2008 and all of them were included in this study. Private hospitals were not included in this study due to the difficulties in obtaining data despite they had some effects in health care services of regional hospitals but not in medical education services. University hospitals were included in one dummy variable for regression analysis to identify the factors affecting on the efficiency of regional hospitals (determinants of hospital efficiency). Data were available for all 25 regional hospitals in both years as inclusion criteria; in addition, there were no exclusion criteria and no missing data.

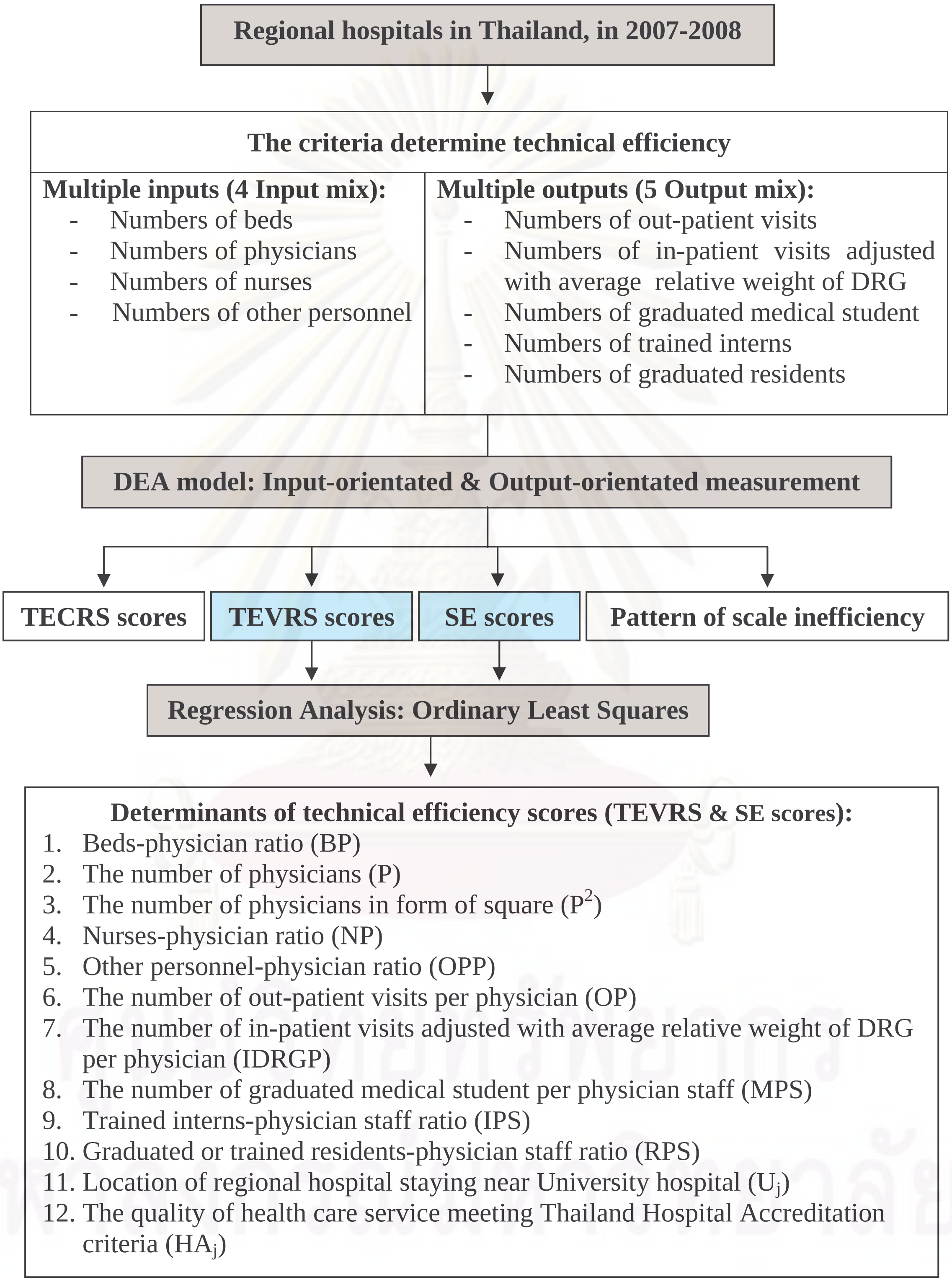
3.3 Conceptual framework

The study consists of two stages. The first stage is to measure the technical efficiency of regional hospitals in Thailand with the data envelopment analysis (DEA) using input-orientated and output-orientated measurement. The results of DEA will show technical efficiency (TE) or technical efficiency under constant return to scale assumption (TECRS) scores, pure technical efficiency or technical efficiency under variable return to scale (TEVRS) scores, scale efficiency (SE) scores, and the patterns of scale inefficiencies which have two patterns of scale inefficiencies that are increasing return to scale (irs) and decreasing return to scale (drs).

The second stage is to identify the factors affecting on the efficiency of regional hospitals (determinants of hospital efficiency) with regression analysis using ordinary least squares (OLS). Technical efficiency under variable return to scale assumption (TEVRS) and scale efficiency (SE) are dependent variables and twelve explanatory variables will be estimated the magnitude and direction of their relation.

All method of analyses can be concluded in conceptual framework as Figure 3-1 below.

Figure 3-1 Conceptual framework



3.4 Type of data

Most secondary panel data and one primary panel data from were collected since 2007-2008. One primary panel data was the numbers of trained interns which collected from the Medical Council of Thailand.

3.5 Data required

There are conceptual, methodological, and practical problems associated with the evaluation of health care performance with DEA. Conceptualizing clinical performance involves identifying appropriate inputs and outputs. Selecting inputs and outputs raises several questions--Which inputs and outputs should the unit be held accountable? What is the product of a health care provider? Can the outputs be defined while holding quality constant? Should the intermediate and final products be evaluated separately?

Another conceptual challenge involves specifying the technical relationship among inputs. Within the boundaries of current professional knowledge, there are varieties of best practices. Consequently, an evaluation model should distinguish best practices from alternative practice styles.

There are some problems about choice of inputs and outputs, and especially finding an “acceptable” concept of product/service. Which inputs and outputs should physicians be held accountable? In addition, there are other issues about measures and concepts; for example:

- Defining models from stakeholder views
- Selection of inputs and outputs
- Should inputs include environmental and organizational factors?
- Problems on the best practice frontier
  - Are the input factors in medical services substitutable?
  - Are constant or variable returns to scale?
  - Do economies of scale and scope exist? (Cooper, Seiford, & Zhu, 2004: 503-504)

Input categories

1. Beds

The number of fully staffed hospital beds is most often used as a proxy for hospital size and capital investment. Several studies included the number of beds as an input category. Several studies disaggregated hospital beds into acute beds, intensive care unit (ICU) beds, long-term beds, and the number of beds, number of bed-days available, pediatric beds, obstetric beds, psychiatric beds, other special beds, and wards.

2. Clinical staff

About two-thirds of hospitals operating costs were due to payroll expenses. Labor costs varied significantly by geographic region; hence, the majority of studies included the ‘number of clinical staff’ as a proxy for ‘labor costs’. Most studies did not include ‘clinical staff’ used ‘labor costs’ instead. Hospital clinical staff consists of physicians, nurses, and other health/medical personnel. Several studies disaggregated ‘physicians’ into ‘specialist’ and ‘generalist physicians’, ‘medical residents’, and the ‘surgeons’. The nursing category has been further disaggregated into ‘registered nurses,’ and ‘licensed practical nurses’ in several studies. Some studies defined ‘number of personnel’ as a general labor input category. Some studies assigned atypical clinical labor parameters to inputs. These included ‘trained, learning, and other nurses,’ ‘junior and senior non-nursing medical and dental staff,’ and ‘professional, technical, administrative, and clerical staff’.

3. Non-clinical staff

Several studies included the number of ‘non-clinical staff’ as a hospital input. This category included ‘technical, managerial, and other staff’.

4. Working hours

The ‘‘number of working hours’’ was a seldom-used input category for hospital efficiency analyses.

5. Services offered

The number of hospital services had also been used as a proxy for capital investment. This was most common for studies of US hospitals since the necessary data were published in the American Hospital Association (AHA) annual survey. In the non-US studies, however, this category was generally not included as input.

6. Costs

The bulk of a hospital’s operating costs are due to labor and salaries and other expenses that vary significantly by geographic region. Accurate data on capital investment is difficult to obtain, creating the need to use proxy categories, such as ‘beds’ and ‘services.’ Thus, practical considerations have often precluded the use of cost data. Nevertheless, many studies have included various types of cost data in their input set. These can be divided into the following subcategories: ‘operating expenses and capital investment’, ‘labor costs’, and ‘supply and non-labor costs’.

6.1 Operating expenses and capital investment

Some studies included ‘operating expenses excluding payroll, capital, net plant assets, total annual expenditures, capital assets, capital costs, total other inpatient charges, total other expenses, and total depreciation’ as an input category.

6.2 Labor costs

Most studies omitted ‘labor expenses’ since these vary significantly by region. Both US and non-US studies accounted for this category at similar levels of use. Staff costs were variously sub-divided into ‘general labor,’ ‘nursing staff,’ ‘medical staff,’ and ‘other staff.’ Some studies used a regional adjustment factor to control for local variation in wage rates.

6.3 Supply and non-labor costs

‘Supply and non-labor costs’ were included as an input category twice as frequently in non-US studies since US-based efforts generally employed ‘operating expenses’. These costs were variously sub-divided into equipment costs, medical supply costs, food costs, drug and pharmaceutical costs, material costs, non-labor costs, and other costs. Several authors employed ‘medical supply costs’ and ‘drug and pharmaceutical costs’ in their input data set.

7. Atypical and specific input categories

Atypical input categories were found such as cubic meters of the hospital building, type of ownership, labor hours per average daily census, cost index, revolving funds expenditure, number of full-time-equivalents excluding physicians,

physicians and dentists on salary, physicians on the medical staff, and teaching full-time-equivalents.

Output categories

1. Medical visits, cases, patients, and surgeries

The vast majority of studies included outpatient visits and some studies disaggregated outpatient visits into ‘emergency’ and ‘non-emergency’. Some studies included ‘surgeries’ as an output factor, while some studies distinguished between ‘inpatient surgeries’ and ‘outpatient surgeries’.

2. Inpatient days

Prior to 1983, American hospitals were reimbursed based primarily on total costs; hence, there was little incentive to reduce patient length of stay. This changed with the implementation of the Prospective Payment System based on DRGs. Under the new system, the hospital would be paid the same amount for each Medicare patient within a DRG category, regardless of the costs incurred. This represented a significant shift from the ‘inpatient day’ to the ‘case’ as the primary means of hospital reimbursement. The ‘gold standard’ in the US for measuring inpatient activity was DRG-adjusted discharges. In contrast, the reimbursement systems in European countries were more complex and varied. Within the last decade, several countries, such as Austria, Germany, Norway, Spain, and the UK, had moved from ‘cost-based’ to more ‘case-based’ reimbursement in order to better control health care expenditures. Europe had thus followed the lead of the US DRG-system by introducing elements of competition and ‘deregulation’ into hospital financing. Hence, a shift away from ‘patient days’ toward ‘adjusted discharges’ was expected a measure of hospital output.

3. Admissions, discharges, and services

Only a handful of studies, mainly non-US efforts, used the ‘number of admissions’ as an output factor. Several studies included DRG-adjusted discharges either as a single output category or as part of their larger output set. A few studies used intermediate hospital products as outputs, such as ancillary services and laboratory examinations.

4. Atypical, teaching, and specific output categories

Several US studies addressed the problem of how to compare teaching and non-teaching hospitals. Thus, hospital teaching can be viewed as both a labor input and a teaching and research output. Some studies included teaching sub-categories in their efficiency analyses. For example, these used number of nursing students, number of interns, number of residents, clinical training weeks of nurses, clinical training weeks of medical students, sum of medical and dental trainee full time equivalents, other professional trainee full time equivalents, number of teaching full-time equivalent staff, and dollars spent on graduate medical education. Some studies measured hospital research as the number of scientific publications (O’Neilla, Raunerb, Heidenbergerb, & Kraus, 2008: 171-183).

Data of this study was prepared for both DEA and regression analysis. There were four multiple inputs for DEA such as numbers of beds, numbers of physicians, numbers of nurses and numbers of other personnel. These inputs were the essential input factors for health care and medical education services. There were five multiple outputs for DEA such as numbers of out-patient visits, numbers of in-patient visits adjusted with relative weight of DRG (in-patient visits*DRG), numbers of graduated medical student, numbers of trained interns and numbers of trained residents. There were two kinds of outputs; the first two outputs were intermediate products provided for health care services and the remaining outputs were final outcomes provided for medical education services. The final outcomes of health care services were impossible for data collection such as number of cured patients, disability, etc. The efficiency measurement should be based on true health outcomes data rather than production data (immediate outputs e.g. number of patients treated, bed-days, in-patient visits). However, because of the incompleteness of available health outcomes data, this aspect of performance of a health system or even an individual unit within the health system is difficult to measure. For example, a complete listing of outcomes due to different hospital treatments would require a large number of indicators and highly tedious computations and statistical analyses. On the other hand, the output measurement based on various activities may provide a useful means to assess and compare the technical aspect of hospital production (productivity and technical efficiency measurement based on intermediate types of output such as the DRGs). While the number of treated patients or the numbers of bed-days are more easily measured than health outcomes, there still remains the problem of variations in case-mix, both across individual hospitals, over time, and across health care systems (Linna, Hakkinen, & Magnussen, 2006: 269; Linna, 1998: 419). In health care after patients are admitted to a care facility (or visit a clinic) there are three major clinical processes: (1) investigation/diagnosis, (2) treatment/therapy, and (3) recovery (Cooper, Seiford, & Zhu, 2004: 492). The outputs of this study included all three processes of in-patients care. These outputs could assume that holding quality constant because both processes; in health care and medical education services, were under quality assurance and the observations in this study were homogeneity. Physician was the most important factor of the first two outputs and physician staff was the most important factor of the remaining outputs. In addition, there were twelve explanatory variables for regression analysis such as beds-physician ratio (BP), numbers of physicians (P), numbers of physicians in form of square (P^2), nurses-physician ratio (NP), other personnel-physician ratio (OPP), trained interns-physician staff ratio (IPS), graduated residents-physician staff ratio (RPS), out-patient visits per physician (OP), in-patient visits adjusted with relative weight of DRG per physician (IDRGP), graduated medical student per physician staff (MPS), and two dummy variables; location of regional hospital staying near University hospital (U_j) and quality of health care service meeting Thailand Hospital Accreditation criteria (HA_j). These determinants included environmental and organizational factors as both dummy variables. This study design provides for stakeholder and health care provider views. In summary, the data of this study was divided into three groups such as aggregated inputs, aggregated outputs and interesting factors.

Aggregated inputs

There were five aggregated inputs of data required in this study and these entire secondary panel data from the year 2007-2008 were the numbers of beds, physicians, physician staffs, nurses and other personnel. The details of each aggregated input, abbreviation, operational definition and its unit were presented in Table 3-1 below.

Table 3-1 Aggregated inputs, abbreviations, operational definitions and units

Aggregated inputs	Abbr.	Operational definitions	Units
Numbers of beds in hospital ***i*** in year ***t***	B_{it}	counted for every beds for in-patient services in each regional hospital in year 2007 and 2008	beds
Numbers of physicians in hospital ***i*** in year ***t***	P_{it}	counted for every physicians in each regional hospital in year 2007 and 2008 (including interns, refunding physicians, residents and dentists)	persons
Numbers of physician staffs in hospital ***i*** in year ***t***	PS_{it}	counted for every physician staffs in each regional hospital in year 2007 and 2008 (not including interns, refunding physicians, residents and dentists)	persons
Numbers of nurses in hospital ***i*** in year ***t***	N_{it}	counted for every registered and technical nurses in each regional hospital in year 2007 and 2008	persons
Numbers of other personnel in hospital ***i*** in year ***t***	OP_{it}	counted for every other personnel in each regional hospital in year 2007 and 2008 (not including physicians, dentists and nurses)	persons

NOTE: Abbr. = abbreviations

Aggregated outputs

There were six aggregated outputs of data required in this study. They were five secondary panel data and one primary panel data from the year 2007-2008 such as the numbers of out-patient visits, in-patient visits, adjusted average relative weight of diagnostic related group (DRG), graduated medical student, trained interns and graduated or trained residents. The details of each aggregated input, abbreviation, operational definition and its unit were presented in Table 3-2 below.

Table 3-2 Aggregated outputs, abbreviations, operational definitions and units

Aggregated inputs	Abbr.	Operational definitions	Units
Numbers of out-patient visits in hospital *i* in year *t*	O_{it}	counted for every visit in out-patient department for whole year in each regional hospital in year 2007 and 2008 (including dental clinic and extra-time clinic visits)	visits
Numbers of in-patient visits in hospital *i* in year *t*	I_{it}	counted for every visit that was admitted in in-patient care units for whole year in each regional hospital in year 2007 and 2008	visits
Adjusted average relative weight of diagnostic related group (DRG) in hospital *i* in year *t*	DRG_{it}	the proxy of related-patient types treated to the resources they consumed in each regional hospital in year 2007 and 2008	-
Numbers of graduated medical student in hospital *i* in year *t*	MS_{it}	counted for every graduated medical student in each regional hospital in year 2007 and 2008	persons
Numbers of trained interns in hospital *i* in year *t*	I_{it}	counted for every trained intern in each regional hospital in year 2007 and 2008	persons
Numbers of graduated or trained residents in hospital *i* in year *t*	R_{it}	counted for every graduated or trained residents in each regional hospital in year 2007 and 2008	persons

Interesting factors

There were two interesting factors of data required in this study and they were dummy variables. These entire secondary panel data from the year 2007-2008 were the location of regional hospital staying near University hospital or not (U_i) and the quality of health care service meeting Thailand Hospital Accreditation criteria or not (HA_i). The details of interesting factor, abbreviation, operational definition and its unit were presented in Table 3-3 below.

University hospital was a good alternative of health care services for patients but limited by the payment system. In addition, University hospital was a good alternative of medical education services for admission of high school student to study Bachelor in Medicine and collaborated with regional hospital to teach medical student. So University hospital had the impact to regional hospitals in both health care services and medical education services.

Thailand Hospital Accreditation criteria were the proxy of the quality of health care services which helped to guarantee the process of health care services of the hospital which meeting this criteria was good enough to trust.

Table 3-3 Interesting factors, abbreviations, operational definitions and units

Interesting factors	Abbr.	Operational definitions	Units
Location of each regional hospital staying near University hospital or not in hospital *i* in year *t*	U_j	- the proxy of competitive hospital in health care services;	-
	U_{0it} (j = 0)	- regional hospital *i* did not stay near University hospital in year *t*	
	U_{1it} (j = 1)	- regional hospital *i* stayed near University hospital in year *t*	
Quality of health care service considers each regional hospital meeting Thailand Hospital Accreditation criteria or not in hospital *i* in year *t*	HA_j	- the proxy of the quality of health care services;	-
	HA_{0it} (j = 0)	- regional hospital *i* did not meeting Thailand Hospital Accreditation criteria in year *t*	
	HA_{1it} (j = 1)	- regional hospital *i* met Thailand Hospital Accreditation criteria in year *t*	

3.6 Sources of data

All secondary and primary panel data are annual report of hospitals from many data sources for more valid and reliable data used for calculation. The details of data required, types of data and sources of data were presented in Table 3-4 below.

Table 3-4 Data required, types of data and sources of data

Data required	Types of data	Sources of data
Numbers of beds, out-patient visits, in-patient visits, and Adjusted average relative weight of diagnostic related group (DRG)	secondary	• Bureau of health service system development, Department of Health Service Support, Office of the Permanent Secretary, Ministry of Public Health (MoPH)
Numbers of practicing physician staffs, interns refunding physicians, residents and dentists,	secondary	• All regional hospitals in Thailand • Personnel Administration Division, Office of the Permanent Secretary, Ministry of Public Health
Numbers of physicians, nurses (registered and technical nurses), other personnel	secondary	• All regional hospitals in Thailand
Numbers of graduated medical student	secondary	• Collaborative Project to Increase Production of Rural Doctor (CPIRD) • All regional hospitals in Thailand
Numbers of trained interns	primary	• The Medical Council of Thailand
Numbers of graduated or trained residents	secondary	• The Medical Council of Thailand • The Royal College of Physician of Thailand • The Royal College of Surgeons of Thailand • The Royal College of Pediatricians of Thailand • The Royal Thai College of Obstetricians and Gynaecologists • The Royal College of Orthopaedic Surgeons of Thailand • The Royal College of Orthopaedic Surgeons of Thailand • Thai Association for Emergency Medicine • All regional hospitals in Thailand
Location of each regional hospital staying near University hospital or not	secondary	• All regional hospitals in Thailand
Quality of health care service considers each regional hospital meeting Thailand Hospital Accreditation criteria	secondary	• The Healthcare Accreditation Institute (Public Organization) • All regional hospitals in Thailand

3.7 Analysis technique

This study consists of two stages.

1. Data envelopment analysis (DEA) using input-orientated and output-orientated measurement. This study used four multiple inputs and five multiple outputs being data for calculation using DEAP version 2.1; a data envelopment analysis (computer) program, designed by Coelli Tim. The results provided technical efficiency under constant return to scale assumption (TECRS) scores, technical efficiency under variable return to scale (TEVRS) scores, scale efficiency (SE) scores, and the patterns of scale inefficiencies.
2. Regression analysis using ordinary least squares (OLS). Some results of DEA; TEVRS scores and SE scores, were used as dependent variables of regression analysis using ordinary least squares (OLS) and these technical efficiency scores were regressed against a set of twelve explanatory variables. The regression models were estimated by EViews and the results of OLS regression analysis revealed the estimation models which provided the magnitude and direction of the factors affecting on the efficiency scores of regional hospitals (determinants of hospital efficiency).

The details of DEA results and estimated regression models were analyzed by SPSS for Windows.

3.8 Model specification

3.8.1 Data envelopment analysis (DEA) model

In health care sector, there are a lot of studies of input-orientated measurement DEA but there are some studies of output-orientated measurement DEA (for example; Chang, Cheng, & Das, 2004; Afonso & Fernandes, 2008). Input-oriented measurement DEA assumes that the firm can change quantities of inputs, while quantities of outputs are fixed, to meet the most efficient point. In the reverse, output-orientated measurement DEA assumes that quantities of outputs can change to match with the most efficiency point while quantities of inputs are fixed.

- **Input-orientated measurement DEA.** Evaluating a health care provider's clinical efficiency requires an ability to find "best practices"--i.e., the minimum set of inputs to produce a successfully treated patient. Technical inefficiency occurs when a provider uses a relatively excessive quantity of clinical resources (inputs) when compared with providers practicing with a similar size and mix of patients. Scale inefficiency occurs when a provider operates at a sub-optimal activity level--i.e., the unit does not diagnose and/or treat the most productive quantity of patients of a given case mix. Hence, hospital providers will be considered 100% efficient if they cared for patients with fewer days of stay and ancillary services and at an efficient scale size. Primary care providers will be considered efficient if they cared for their patients with fewer visits, ancillary tests, therapies, hospital days, drugs, and sub-specialty consults. Clinical inefficiency in the provision of health care services occurs when a provider uses a relatively excessive quantity of clinical inputs when compared with providers treating a similar case load and mix of patients (Cooper, Seiford, & Zhu, 2004: 493). Input-orientated measurement DEA studies are:

1) Clinical efficiency requires patient management—i.e., physician decision making that utilizes a minimal quantity of clinical resources to achieve a constant quality outcome, when caring for patients with similar diagnostic complexity and severity.
2) Allocative efficiency is the efficiency analysis of situations in which unit prices and unit costs are available and the objective is to minimize the total cost of satisfying the output constraints (Cooper, Seiford, & Zhu, 2004: 27-28).
3) Cost efficiency deals with a combination of technical and allocative efficiency. An organization will only be cost efficient if it is both technically and allocatively efficient. Cost efficiency is calculated as the product of the technical and allocative efficiency scores (expressed as a percentage), so an organization can only achieve a 100 per cent score in cost efficiency if it has achieved 100 per cent in both technical and allocative efficiency (Bhat, Verma, & Reuben, 2001: 310-311).

- **Output-orientated measurement DEA.** Most simply, technical inefficiency refers to the extent to which a decision-making unit (DMU) fails to produce maximum output from its chosen combination of factor inputs, and scale inefficiency refers to sub-optimal activity levels. Output-orientated measurement DEA studies are:

1) Managerial efficiency requires practice management—i.e., achieving a maximum output from the resources allocated to each service department, given clinical technologies.
2) Profitability models. There is a need to do more performance studies that look at revenue and expenses, and investigate the factors affecting profitability especially in profit hospitals. Since the performance measure, takes the form of Profit = Revenues – Expenses; which can be interpreted as maximizing profit, or maximizing an excess of revenue over expenses. In these studies, the maximum profit includes actual profit, plus maximum overall inefficiency (Cooper, Seiford, & Zhu, 2004: 502-503).
3) The Malmquist index is one of the most frequently used techniques to measure productivity changes over time. This approach commonly employs the output-oriented DEA model. For this approach, a score of less than one indicates technological progress, whereas a score greater than one indicates regress. In this regard, Fare et al. investigated 17 Swedish hospitals and found a wide variation in performance during the period 1970–1985. Technical inefficiency was present while technical regress was fairly common. A recent study by O'Neill and Dexter used an output-oriented DEA model to identify best practices in market capture for eight different surgical specialties. The goal was to increase surgical volumes by identifying overlooked surgical markets (O'Neilla et al., 2008: 163 and 171).

The reasons of this thesis using output-orientated DEA (fixed quantities of inputs) instead of input-orientated DEA (fixed quantities of outputs) are the insufficient resources including personnel (physicians and nurses), budgets and medical equipments. The main factor was deficiency of physicians who required time in training program for 3-5 years because the Ministry of Public Health had policy that only specialists and sub-specialists can practice in regional hospital in Thailand. The problems of physicians can not tolerate to face the workload (over demand of health care services), inadequate medical equipments, a lot of stress from the high expectation of patients and relatives, and low incentives. Although the Ministry of Public Health tried to increase the quota of physicians to regional hospitals but the physicians still leave from these hospitals continuously (brain-drain problem) to private hospitals that gave more incentives and practiced with less workload. The second main factor was deficiency of nurses in regional hospitals because Thailand government limited the civil servant system and tried to decrease the numbers of civil servants so new nurses could not register to this system and many new nurses drained to private sector which gave more incentives. Among these situations, a good hospital management or efficient hospital management is one of major solutions to solve these problems. In addition, the chance of increasing of physician staffs, nurses and budgets in regional hospitals in those years was not easy like input fix so measuring the maximum of output mix fit to output-orientated DEA as managerial efficiency.

Input mix

The classical economics focuses on physical resources in defining its factors of production which are land (natural resources), labor (human effort), and capital (machinery, tools and buildings). In this study, the inputs of regional hospitals considered the number of beds as the proxy of hospital size as capital input, and all levels of personnel as labor input. There were four multiple inputs used in this study.

1. The numbers of beds in hospital *i* in year *t*; B_{it},
2. The numbers of physicians in hospital *i* in year *t*; P_{it},
3. The numbers of nurses in hospital *i* in year *t*; N_{it},
4. The numbers of other personnel in hospital *i* in year *t*; P_{it}.

Output mix

All regional hospitals in Thailand must provide health care services but some regional hospitals with high competency and willingness to joint medical education services can joint in case of passing quality assurance of medical education in each level. Some regional hospitals did not joint in all level of medical education services. Some regional hospitals jointed in some level of medical education services; undergraduate level (medical student teaching program) or/and postgraduate level (intern training and resident training programs). There were maximum seven residency training programs which some regional hospitals can train by themselves and collaborate with the Faculty of Medicine in Universities such as General Medicine, General Surgery, General Pediatric, Obstetric and Gynecology, Orthopaedic Surgery, Family Medicine, and Emergency Medicine. In this study used five multiple outputs as following.

1. The numbers of out-patient visits in hospital *i* in year *t*; O_{it}, were the proxies of out-patient health care services in each hospitals.

2. The numbers of in-patient visits adjusted with average relative weight (RW) of diagnostic related group (DRG) in hospital *i* in year *t*; $IDRG_{it}$, were the proxies of in-patient health care services adjusted with the consumed resources in each hospitals in each year (the numbers of in-patient visits multiplied by adjusted average RW of DRG). For in-patient visits adjusted with average RW of DRG of each hospital were used to calculate instead of in-patient visits alone because this reflected the competency of health care services in each hospital better than in-patient visits alone.
3. The numbers of graduated medical student in hospital *i* in year *t*; M_{it}, were the proxies of undergraduate level teaching in clinical years of medical student.
4. The numbers of trained interns in hospital *i* in year *t*; I_{it}, were the proxies of intern training program using 1 year for training.
5. The numbers of graduated residents in hospital *i* in year *t*; R_{it}, were the proxies of resident training program using 3-5 year for training.

Since DEA is a non-parametric technique, statistical hypothesis tests are difficult and this is one of limitations of DEA (Bhat, Verma, & Reuben, 2001: 321).

3.8.2 Regression analysis using ordinary least squares (OLS)

Simple linear regression model using ordinary least square estimation provides more details about the factors affecting on the technical efficiency scores of regional hospitals (determinants of hospital efficiency). The efficiency scores from the calculation using DEA are postulated from the assumption of homogenous inputs, outputs and operating characteristics. But each of them had varieties in each item. In order to identify and evaluate the impact of idiosyncratic determinants on efficiency, the efficiency scores perform as the dependent variables while the explanatory variables represent as the hospital efficiency determinants.

Determinants of hospital efficiency

There were twelve explanatory variables as following:

1) Bed-physician ratio
2) The numbers of physicians
3) The numbers of physicians in form of square
4) Nurses-physician ratio
5) Other personnel-physician ratio
6) Trained interns-physician staff ratio
7) Graduated residents-physician staff ratio
8) Out-patient visits-physician ratio
9) In-patient visits adjusted with average relative weight of diagnostic related group (DRG)-physician ratio
10) Graduated medical student-physician staff ratio
11) Location of each regional hospital staying near University hospital
12) Quality of health care service considers each regional hospital meeting Thailand Hospital Accreditation criteria.

Technical efficiency under variable return to scale assumption (TEVRS) scores and scale efficiency (SE) scores from DEA evaluation were used as dependent variables and twelve explanatory variables were estimated the magnitude and direction of their relation.

1) Relation between explanatory variables and TEVRS scores

$$\text{TEVRS scores}_{it} = c_0 + c_1{*}BP_{it} + c_2{*}P_{it} + c_3{*}P_{it}^2 + c_4{*}NP_{it} + c_5{*}OPP_{it} + c_6{*}IPS_{it} + c_7{*}RPS_{it} + e \quad (3\text{-}1)$$

where TEVRS = technical efficiency score under variable return to scale assumption of hospital *i* in year *t*

c_0 = constant c_1 = coefficient of BP_{it} c_2 = coefficient of P_{it}

c_3 = coefficient of P_{it}^2 c_4 = coefficient of NP_{it} c_5 = coefficient of OPP_{it}

c_6 = coefficient of IPS_{it} c_7 = coefficient of RPS_{it} e = error term.

Table 3-5 Explanatory variables of TEVRS scores, abbreviations and operational definitions

Explanatory variables of TEVRS scores	Abbr.	Operational definitions
Bed-physician ratio of hospital *i* in year *t*	BP_{it}	The proportion of numbers of beds and numbers of physicians (beds/physician) was a proxy for size determination of input combination between bed and physician.
Numbers of physicians in hospital *i* in year *t*	P_{it}	The proxy for labor inputs which were considered as the most important labor inputs for health care services and medical education services.
Numbers of physicians in hospital *i* in year *t* in form of square	P_{it}^2	This form of square in equation used to find out the maximum/ minimum numbers of physicians to provide TEVRS scores.
Nurses-physician ratio of hospital *i* in year *t*	NP_{it}	The proportion of numbers of nurses and numbers of physicians (nurses/physician) was a proxy for size determination of input labor combination between nurse and physician.
Other personnel-physician ratio of hospital *i* in year *t*	OPP_{it}	The proportion of numbers of other personnel and numbers of physicians (other personnel/physician) was a proxy for size determination of input labor combination between other personnel and physician.
Trained interns-physician staff ratio in hospital *i* in year *t*	IPS_{it}	The proportion of numbers of trained interns and numbers of physician staffs (trained interns/physician staff) was a proxy for output of postgraduate medical education services in intern training program by physician staff.
Graduated residents-physician staff ratio in hospital *i* in year *t*	RPS_{it}	The proportion of numbers of graduated residents and numbers of physician staffs (graduated residents/physician staff) was a proxy for output of postgraduate medical education services in residency training program by physician staff.

All explanatory variables affected the technical efficiency of regional hospitals. The major factor of health care services was physician so all explanatory variables about inputs and outputs of health care services which were numerical used in form of ratio or proportion of numbers of physicians as denominator to eliminate the variation of different size of regional hospitals. In addition, the major factor of medical education services was physician staffs so all explanatory variables about outputs of medical education services which were numerical used in form of ratio or proportion of numbers of physician staffs as denominator to eliminate the variation of different size of regional hospitals too.

The rationale for inclusion of the explanatory variables of TEVRS scores:

- Beds-physician ratio (BP). This proportion showed the combination of input between bed (as a capital input) and physician (as a labor input). There were over demand in health care services in regional hospitals related to insufficient health care providers especially physicians. So one physician can manage more in-patient visits or more beds that meant more hospital efficiency but this assumption was limited by the quality of service because if there were too many beds for one physician to manage, it revealed the negative outcome because of poor quality results or the inefficient hospital management. The sign of beds-physician ratio may be positive or negative depending on the situation of hospital; if it showed a positive sign meaning one physician can increase the numbers of beds for service and will increase hospital efficiency because of the over supply of physicians relative to the numbers of beds, but if it showed a negative sign meaning one physician should decrease the numbers of beds for service and will increase hospital efficiency because of the workload's problem of physician or the over supply of beds relative to the numbers of physicians, giving other things were constant. For the situation of the whole picture of regional hospitals in Thailand in year 2007-2008, the expected sign should be negative or this explanatory variable was expected to have a negative relationship with TEVRS scores because of the workload's problem of physician. This assumption was the same as the previous study (Kornpob Bhirombhakdi, 2008).

- The numbers of physicians (P). Physician was the most important labor factor of both health care services and medical education services of regional hospitals so this explanatory variable should consider in separate term. The higher in the numbers of physicians will provide the more outputs of health care services and medical education services but if the numbers of physicians were too much, it will show the inefficient hospital management. The sign of numbers of physicians may be positive or negative depending on the situation of hospital; if it showed a positive sign meaning an increasing in one physician will increase TEVRS scores because of the workload's problem of physician but if it showed a negative sign meaning an increasing in one physician will decrease TEVRS scores because of the over supply of physicians relative to other inputs, giving other things were constant. This explanatory variable was expected to have a positive relationship with TEVRS scores because of the workload's problem of physician.

- The numbers of physicians in form of square (P^2). This square term of numbers of physicians in parabolic function of TEVRS scores presented the minimum or maximum of TEVRS scores when the numbers of physicians changed. The sign of numbers of physicians in form of square may be positive or negative depending on the situation of hospital; if this term showed a positive sign meaning the result will show the minimum of TEVRS scores, but if it showed a negative sign meaning the result will show the maximum of TEVRS scores, giving other things were constant. The maximum of TEVRS scores always equals 1.000 and the performance of most regional hospitals is good so the expected sign should be positive because it will show the minimum of TEVRS scores. This explanatory variable was expected to have a positive relationship with TEVRS scores.

- Nurses-physician ratio (NP). This proportion showed the combination of input labor between nurse and physician. Most of regional hospitals face with the problem of lack of both labor groups; physicians and nurses, but the severity of physician insufficiency or nurse insufficiency can not compare because no evidence supported. Nurses were the complementary unit of physicians in some health care services and medical education services but nurses sometimes were the substitute for physicians in some situations. The sign of nurses-physician ratio may be positive or negative depending on the situation of hospital; if it showed a positive sign meaning an increasing in the numbers of nurses for service will increase hospital efficiency because of the deficiency's problem of nurses, but if it showed a negative sign meaning an decreasing in the numbers of nurses for service will increase hospital efficiency because of the over numbers of nurses relative to the numbers of physicians. The expected sign should be positive or this explanatory variable was expected to have a positive relationship with TEVRS scores because of the deficiency's problem of nurses. This assumption was the same as the previous study (Kornpob Bhirombhakdi, 2008).

- Other personnel-physician ratio (OPP). This proportion shows the combination of input between other personnel and physician. The optimal ratio of other personnel and physician for regional hospitals never study before. Other personnel were only complementary unit of physicians in some health care and medical education services. The sign of other personnel-physician ratio may be positive or negative depending on the situation of hospital; if it showed a positive sign meaning an increasing in the numbers of other personnel for service will increase hospital efficiency because of the deficiency's problem of other personnel, but if it showed a negative sign meaning an decreasing in the numbers of other personnel for service will increase hospital efficiency because of the over numbers of other personnel relative to the numbers of physicians. The expected sign should be positive or this explanatory variable was expected to have a positive relationship with

TEVRS scores because of the deficiency's problem of other personnel. This assumption liked the previous study (Kornpob Bhirombhakdi, 2008).

- Trained interns-physician staff ratio (IPS). Interns are physicians who practice and get skill training in regional hospitals for one year and they can help physician staffs in both health care and medical education services so they are important input labor. There are no definite interns-physician staff ratio for intern training program in regional hospitals but many factors are considered such as the numbers of beds, the numbers of out-patients and in-patients, varieties of cases, numbers of clinical year medical student, numbers of residents, etc. The sign of trained interns-physician staff ratio may be positive or negative depending on the situation of hospital; if it showed a positive sign meaning an increasing in the numbers of interns will increase hospital efficiency because physician staff in regional hospitals had a capacity to train more interns, but if it showed a negative sign meaning an decreasing in the numbers of interns will increase hospital efficiency because of the workload's problem of physician staff. The expected sign should be positive or this explanatory variable was expected to have a positive relationship with TEVRS scores because the numbers of trained interns still were a small numbers.

- Graduated residents-physician staff ratio (RPS). Residents are physicians who practice and get knowledge and skill in each specialty of training program in regional hospitals for 3-5 years and they can help physician staffs in both health care and medical education services more than interns so they are very important input labor. The last year residents can act as physician staffs in many situations. There are different in ratio of residents and physician staff for each residency training program in regional hospitals and many factors are considered for each specialty of training program such as the numbers of beds, the numbers of out-patients and in-patients, varieties of cases, numbers of physician staffs in that field, etc. The sign of graduated or trained residents-physician staff ratio may be positive or negative depending on the situation of hospital; if it showed a positive sign meaning an increasing in the numbers of residents will increase hospital efficiency because physician staff in regional hospitals had a capacity to train more residents, but if it showed a negative sign meaning an decreasing in the numbers of residents will increase hospital efficiency because of the workload's problem of physician staff. The expected sign should be positive or this explanatory variable was expected to have a positive relationship with TEVRS scores because the numbers of trained residents still were a small numbers.

The expected signs of all explanatory variables of TEVRS scores were summarized in Table 3-6 below.

Table 3-6 The expected signs of explanatory variables of TEVRS scores

Dependent variables	Explanatory variables of TEVRS scores						
	BP_{it}	P_{it}	P_{it}^2	NP_{it}	OPP_{it}	IPS_{it}	RPS_{it}
TEVRS $scores_{it}$	-	+	+	+	+	+	+

2) Relation between explanatory variables and scale efficiency (SE) scores

SE scores$_{it}$ = $c_0 + c_1{*}OP_{it} + c_2{*}IDRGP_{it} + c_3{*}MPS_{it} + c_4{*}U_{1it} + c_5{*}HA_{1it} + e$ (3-2)

where SE = scale efficiency of hospital ***i*** in year ***t***

c_0 = constant c_1 = coefficient of OP_{it} c_2 = coefficient of $IDRGP_{it}$

c_3 = coefficient of MPS_{it} c_4 = coefficient of U_{1it} c_5 = coefficient of HA_{1it}

e = error term.

Table 3-7 Explanatory variables of SE scores, abbreviations and operational definitions

Explanatory variables of SE scores	Abbr.	Operational definitions
Out-patient visits-physician ratio in hospital ***i*** in year ***t***	OP_{it}	The proportion of numbers of out-patient visits and numbers of physicians (out-patient visits/physician) was a proxy for determining the effect of out-patient service provided by a physician to scale efficiency level.
In-patient visits adjusted with average relative weight (RW) of diagnostic related group (DRG)-physician ratio in hospital ***i*** in year ***t***	$IDRGP_{it}$	The proportion of numbers of in-patient visits adjusted with average RW of DRG and numbers of physicians (in-patient visits adjusted with average RW of DRG/physician) was a proxy for determining the effect of in-patient service adjusted with average RW of DRG provided by a physician to scale efficiency level.
Graduated medical student-physician staff ratio in hospital ***i*** in year ***t***	MPS_{it}	The proportion of numbers of graduated medical student and numbers of physician staffs (graduated medical student/physician staff) was a proxy for output of undergraduate medical education services in medical student teaching by physician staff.

The rationale for inclusion of the explanatory variables of SE scores:

- Out-patient visits-physician ratio (OP). In the large-sized regional hospitals usually have more beds, medical equipments and physicians than the small-sized regional hospitals so one physician in large hospital can manage more varieties of out-patient services than small hospital that means more scale efficiency. One physician can manage more out-patient visits that meant more hospital efficiency but this assumption was limited by the quality of service because if there were too many cases for one physician to manage in out-patient department (OPD), it revealed the negative outcome because of poor quality results or the inefficient hospital management. In fact, regional hospitals in Thailand provide not only tertiary health care service but also primary and secondary health care services which these groups did not need the special treatments as regional hospital level; only general or community hospitals were enough. If the cases of primary and secondary health care services increased more and more, this situation was not good for regional hospitals because it created the workload's problem of physician in regional hospitals. The sign of out-patient visits-physician ratio may be positive or negative depending on the situation of hospital; if it showed a positive sign meaning one physician can increase the numbers of out-patient visits for service and will increase hospital efficiency because of the capacity of large scale of regional hospitals, but if it showed a negative sign meaning one physician should decrease the numbers of out-patient visits for service and will increase hospital efficiency because of the workload's problem of physician, giving other things were constant. The expected sign should be negative or this explanatory variable was expected to have a negative relationship with SE scores because of the workload's problem of physician. This assumption was different from the previous study (Kornpob Bhirombhakdi, 2008) because of the different situation.

- In-patient visits adjusted with average relative weight of diagnostic related group-physician ratio (IDRGP). In the large-sized regional hospitals usually have more beds, medical equipments and physicians than the small-sized regional hospitals so one physician in large hospital can manage more varieties of in-patient services and more complicated or severe cases than small hospital that means more scale efficiency. But in more complicated or severe cases required more personnel, equipments, cost and time for management than the less complicated cases so the numbers of In-patient visits adjusted with average relative weight of diagnostic related group-physician ratio in the large scale regional hospitals may be less than the small scale regional hospitals. One physician can manage more in-patient visits or more beds that meant more hospital efficiency but this assumption was limited by the quality of service because if there were too many in-patient visits for one physician to manage, it revealed the negative outcome because of poor quality results or the inefficient hospital management. In cases of in-patient services of regional hospitals differed from cases of their out-patient services because of the condition of limited numbers of beds and essential equipments in each regional hospital so the criteria for admission in each regional hospital were very strict. In cases of lower than the criteria will be sent back general hospitals and in cases of upper than the criteria will be referred to University hospitals or larger regional hospitals which were more competent. The sign of in-patient visits adjusted with average relative weight of diagnostic related group-physician ratio may be positive or negative depending on the situation of hospital; if it showed a positive sign meaning one physician can increase the numbers of in-patient visits adjusted with average relative weight of diagnostic related group for service and will increase hospital efficiency because of the capacity of large scale of regional hospitals, but if it showed a negative sign meaning one physician should decrease the numbers of in-patient visits adjusted with average relative weight of diagnostic related group for service and will increase hospital efficiency because of the workload's problem of physician, giving other things were constant. The expected sign should be positive or this explanatory variable was expected to have a positive relationship with SE scores because of the capacity of large scale of regional hospitals.

- Graduated medical student-physician staff ratio (MPS). In the large-sized regional hospitals usually have more beds, medical equipments and physicians than the small-sized regional hospitals so one physician staff in large hospital can teach more medical student than small hospital that means more scale efficiency. Medical student teaching usually is the burden of regional hospitals because physical staffs must take more time and more effort in teaching process to produce graduated medical student. The large-sized regional hospitals will decrease the burden of physical staffs in teaching process more than the small-sized regional hospitals because the more personnel, equipments, accessories and budget that will increase scale efficiency. The definite ratio of medical student and physician staff for undergraduate medical education in general set up at 4 medical students per one physician staff. The sign of graduated medical student-physician staff ratio may be positive or negative depending on the situation of hospital; if it showed a positive sign meaning an increasing in the numbers of interns will increase hospital efficiency because physician staff in regional hospitals had a capacity to teach more medical student, but if it showed a negative sign meaning an decreasing in the numbers of medical student will increase hospital efficiency because of the workload's problem of physician staff. The expected sign should be positive or this explanatory variable was expected to have a positive relationship with SE scores because of the number of medical student still were a small numbers.

- Location of each regional hospital staying near University hospital or not (U_j as dummy variable). University hospital usually is a very strong competition of regional hospital in health care services because it has more resources and more competencies in health care services. For health care service perspective, there are different groups of customer in regional hospitals and University hospitals. The major customer group of regional hospital is universal coverage scheme (UC) which follows through referral system. Patients of Social Security Scheme (SSS) are usually received diagnosis and treatment in hospitals which had the signed contract with firms. Patients of Civil Servant Medical Benefit Scheme (CSMBS) and out of pocket payment can choose any hospitals as they want but most of them usually go to University hospital because it is less crowned patients and more competency in treatment than regional hospital. So most of customers of regional hospitals are the poor and the middle class patients while most of customers of University hospitals are the rich and the middle class patients. University hospital has limited beds for in-patients so many cases must be referred to regional hospital which stays in the same province. For medical education perspective, both University hospital and regional hospital help together in medical student teaching and resident training program because University hospital is superior in teaching competencies but it limits in the studied cases for teaching process while regional hospital has more variety of study cases and numbers of cases for practice but it is inferior in teaching competencies. Only new University hospital will be inferior to old regional hospital in the same province. In the large-sized regional hospital usually has more beds, medical equipments and physicians than the small-sized regional hospital but if it stay near University hospital which is very strong competitive and superior to regional hospital, it will take more burden about financial viability and decrease scale efficiency. The sign of location of each regional hospital staying near University hospital as dummy variable may be positive or negative depending on the situation of hospital; if it showed a positive sign meaning location of each regional hospital staying near University hospital will increase scale efficiency because University hospital and regional hospital collaborated together to improve their services, but if it showed a negative sign meaning location of each regional hospital staying near University hospital will decrease scale efficiency because they were strongly competitive so that regional hospital can not fully develop. The expected sign should be positive or this explanatory variable was expected to have a positive relationship with SE scores because in general University hospital and regional hospital collaborate together to improve their services.

- Quality of health care service considers each regional hospital meeting Thailand Hospital Accreditation criteria or not (HA_j as dummy variable). The regional hospitals passed Hospital Accreditation (HA) criteria mean the guarantee of some levels of good quality of health care process and the higher HA level passing shows the more quality improvement of hospital that reflects the more hospital efficiency and scale efficiency. Hospital Accreditation in Thailand has 3 steps; step 1, 2, and 3, the more advance step is the more effort for quality improvement. In the large-sized regional hospitals usually have more beds, medical equipments and physicians than the small-sized regional hospitals so large regional hospital met Thailand Hospital Accreditation criteria can manage more varieties of health care services than small regional hospital met Thailand Hospital Accreditation criteria that means more scale efficiency. The sign of regional hospital meeting Thailand Hospital Accreditation criteria as dummy variable may be positive or negative depending on the situation of hospital; if it showed a positive sign meaning regional hospital meeting Thailand Hospital Accreditation criteria will increase scale efficiency because Thailand Hospital Accreditation criteria support regional hospital to improve their services, but if it showed a negative sign meaning regional hospital meeting Thailand Hospital Accreditation criteria will decrease scale efficiency because Thailand Hospital Accreditation criteria obstruct regional hospital to improve their services. The expected sign should be positive or this explanatory variable was expected to have a positive relationship with SE scores because in general Thailand Hospital Accreditation criteria support regional hospital to improve their services.

The expected signs of all explanatory variables of TEVRS scores were summarized in Table 3-6 below.

Table 3-8 The expected signs of explanatory variables of SE scores

Dependent variables	Explanatory variables of SE scores				
	OP_{it}	$IDRGP_{it}$	MPS_{it}	U_{1it}	HA_{1it}
SE $scores_{it}$	-	+	+	+	+

Hypothesis

H1: Bed-physician ratio was expected to have a negative relationship with TEVRS scores.
H2: The number of physicians was expected to have a positive relationship with TEVRS scores.
H3: The number of physicians in form of square was expected to have a positive relationship with TEVRS scores.
H4: Nurses-physician ratio was expected to have a positive relationship with TEVRS scores.
H5: Other personnel-physician ratio was expected to have a positive relationship with TEVRS scores.
H6: Trained interns-physician staff ratio was expected to have a positive relationship with TEVRS scores.
H7: Graduated residents-physician staff ratio was expected to have a positive relationship with TEVRS scores.
H8: Out-patient visits-physician ratio was expected to have a negative relationship with SE scores.
H9: In-patient visits adjusted with average relative weight of diagnostic related group (DRG)-physician ratio was expected to have a positive relationship with SE scores.
H10: Graduated medical student-physician staff ratio was expected to have a positive relationship with SE scores.
H11: Location of each regional hospital staying near University hospital was expected to have a positive relationship with SE scores.
H12: Quality of health care service considers each regional hospital meeting Thailand Hospital Accreditation criteria was expected to have a positive relationship with SE scores.

3.9 Operational definition of technical efficiency and related words

- Technical efficiency = Situation where it is impossible for a hospital to produce, with the given know how, (1) a larger output from the same inputs or (2) the same output with less of one or more inputs without increasing the amount of other inputs.

- Technical inefficiency = Situation where it is possible for a hospital to produce, with the given know how, (1) a larger output from the same inputs or

(2) the same output with less of one or more inputs without increasing the amount of other inputs.

- Scale efficiency (SE) = the reduction in unit cost available to a firm when producing at a higher output volume.

- Constant return to scale (CRS) = in production, returns to scale refers to changes in output subsequent to a proportional change in all inputs (where all inputs increase by a constant factor). If output increases by that same proportional change in all inputs then there are constant returns to scale (CRTS).
- Increasing return to scale (IRS) = If output increases by more than that proportion change in all inputs.

- Decreasing return to scale (DRS) = If output increases by less than that proportional change in all inputs.

- Diagnosis-related group (DRG) = A system classifies hospital cases into one of approximately 500 groups, also referred to as DRGs, expected to have similar hospital resource use. DRGs are assigned by a "grouper" program based on the International Classification of Diseases (ICD) diagnoses, procedures, age, sex, discharge status, and the presence of complications or co-morbidities. The objective of DRG was to develop a patient classification system that related types of patients treated to the resources they consumed.

- Quality of health care service: meeting Hospital Accreditation (HA) criteria which like the proxy of the quality of health care service. Hospital Accreditation in Thailand divides into 3 steps:
  Step 1 sustains for 1 year
  Step 2 sustains for 1 year
  Step 3 sustains for 2 years
    - 1st Re-accreditation sustains for 3 years
    - 2nd Re-accreditation sustains for 3 years

  In case of expired date of hospital accreditation equals to not pass hospital accreditation criteria. In this study considers only meeting Hospital Accreditation (HA) criteria (or not) and does not concern passing in any steps of Hospital Accreditation (HA) criteria.

CHAPTER IV

RESULTS AND DISCUSSION

This chapter provides the same and different results of both input-orientated and output-orientated measurement DEA and their regression analyses from the same data set in the follow five parts:

1. Descriptive analysis of the input mix and output mix of DEA
2. The results of both input- and output-orientated measurement DEA
3. Descriptive analysis of explanatory variables of regression analysis
4. The results of regression analyses from both input- and output-orientated DEA
5. Discussion

4.1 Descriptive analysis of the input mix and output mix of DEA

Descriptive statistics of input mix data of DEA showed the numbers, mean, standard deviation, minimum, maximum and one-sample Kolmogorov-Smirnov test of input mix of DEA. There were four multiple inputs as presented in Table 4-1 such as beds, total physicians, nurses and other personnel. The numbers of beds of regional hospitals in Thailand in year 2007-2008 were 445-1,019 beds and mean was 705 beds; only three hospitals had lower 500 beds and only one bed had over 1,000 beds as presented in Table A 1. There were 25 regional hospitals in Thailand in year 2007 and 2008. This study uses the data of both years to compare the technical efficiency scores of these two years and to increase the sample size for regression analysis. Each regional hospital in each year was one decision making unit (DMU) and some data did not change in year 2007 and 2008 such as the numbers of bed and one in two dummy variables; location of regional hospital staying near University hospital (U_j) (Table C4), but the others changed in those years. In this study showed that twenty five DMUs in year 2008 can be calculate by DEA (as Table B1) and regression analysis (as Table E1-E4) but the results of regression analysis can not interpret because all coefficients of explanatory variables were insignificant. If there are a small numbers of the samples for regression analysis, the results will show insignificant statistic values so it can not interpret any things. One-sample Kolmogorov-Smirnov test is nonparametric test which prove the interesting data not being a normal distribution if p-value less than 0.005. All of input mix data of DEA were normal distribution.

Table 4-1 Descriptive statistics of input mix of DEA

Descriptive statistics	Input mix of DEA			
	Bed	Total physicians	Nurses	Other personnel
Numbers	50	50	50	50
Mean	704.76	139.90	646.94	1086.22
Standard deviation	168.57	58.61	192.12	327.27
Minimum	445	54	400	356
Maximum	1019	275	1272	1774
One-sample K-S test - Asymp. sig. (2-tailed)	0.377	0.486	0.312	0.905

NOTE: K-S test = Kolmogorov-Smirnov Test

Descriptive statistics of output mix data of DEA showed the numbers, mean, standard deviation, minimum, maximum and one-sample Kolmogorov-Smirnov test of output mix of DEA. There were five multiple outputs as presented in Table 4-2 and 4-3 such as out-patient visits, in-patient visits adjusted with relative weight of DRG (in-patient visits*DRG), graduated medical student, trained interns and trained residents. Every DMU was the intern training hospital (Table A2) but some DMUs were the undergraduate teaching and residency training hospitals which their p-values of one-sample Kolmogorov-Smirnov test were less than 0.005 (not normal distribution). There were 25 DMUs from 50 DMUs which taught undergraduate level combing with health care service (Table A2 and A3) and there were only 19 DMUs from 50 DMUs which had residency training combining with health care service (Table A2 and A4).

Table 4-2 Descriptive statistics of output mix of DEA

Descriptive statistics	Output mix of DEA		
	Out-patient visits	In-patient visits*DRG	Trained interns
Numbers	50	50	50
Mean	528561.04	67082.01	19.56
Standard deviation	133162.54	29816.16	9.14
Minimum	283726	24811.36	7
Maximum	765112	167362.44	46
One-sample K-S test - Asymp. sig. (2-tailed)	0.609	0.228	0.562

Table 4-3 Descriptive statistics of output mix of DEA (not normal distribution)

Descriptive statistics	Graduated medical student	Trained residents
Numbers	50	50
Median	2.00	0.00
Percentile 25^{th}	0.00	0.00
Percentile 75^{th}	22.75	2.50
Minimum	0	0
Maximum	62	21
One-sample K-S test - Asymp. sig. (2-tailed)	0.001	0.000

The details of frequency of graduated medical student in each DMU were presented in Table A3 and the details of frequency of trained residents in each DMU were presented in Table A4.

4.2 The results of both input- and output-orientated measurement DEA

There are three types of technical efficiency scores and one pattern of scale inefficiency provided by DEA program:

1. Technical efficiency under constant return to scale assumption (TECRS) score
2. Technical efficiency under variable return to scale assumption (TEVRS) score
3. Scale efficiency (SE) score
4. Pattern of scale inefficiency is classified into 2 groups which are:
   1) Increasing return to scale (IRS)
   2) Decreasing return to scale (DRS)

4.2.1 Results of both input- and output-orientated DEA

This study explores and compares the results of both input-orientated measurement DEA and output-orientated measurement DEA.

Input-orientated measurement DEA; there were 12 from 25 regional hospitals which had all three efficiency scores (TECRS, TEVRS and SE scores equal to 1) such as hospital number 2, 3, 4, 5, 8, 10, 11, 12, 13, 17, 20, and 23 as Table 4-4 below. There were 4 from 25 regional hospitals which had all three inefficiency scores (TECRS, TEVRS and SE scores less than 1) such as hospital number 9, 16, 19, and 24. In addition, the pattern of scale inefficiency in this group was an increasing return to scale (irs) pattern in both years. There were 4 from 25 regional hospitals which improved their all three efficiency scores (TECRS, TEVRS and SE scores changed from the inefficiency scores in year 2007 to efficiency scores in year 2008) such as hospital number 14, 18, 21 and 22. There were three hospitals which the pattern of scale inefficiency improved from an increasing return to scale (irs) pattern to scale efficiency (hospital number 14, 18, and 21) and only one hospital which improved from a decreasing return to scale (drs) pattern to scale efficiency (hospital number 22).

There were two hospitals which were efficient in TEVRS in both years (TEVRS scores equaled 1 in year 2007-2008) but improved from inefficient hospitals in year 2007 to efficient hospitals in year 2008 by TECRS and SE scores such as hospital number 7 and 25. The pattern of scale inefficiency of hospital number 7 changed from a decreasing return to scale (drs) pattern in year 2007 to scale efficiency in year 2008; however, the pattern of scale inefficiency of hospital number 25 changed from an increasing return to scale (irs) pattern in year 2007 to scale efficiency in year 2008.

Hospital number 1 was efficient in TEVRS in both years (TEVRS scores equaled 1 in year 2007-2008) but reduced from efficient hospitals in year 2007 to inefficient hospitals in year 2008 by TECRS and SE scores. The pattern of scale inefficiency of hospital number 1 changed from scale efficiency in year 2007 to a increasing return to scale (irs) pattern in year 2008.

Hospital number 6 was efficient in TEVRS in both years (TEVRS scores equaled 1 in year 2007-2008) but was inefficient hospitals in both years 2007-2008 by TECRS and SE scores. The pattern of scale inefficiency of hospital number 6 was an increasing return to scale (irs) pattern in both years.

Hospital number 15 was inefficient both TEVRS and TECRS in both years but improved from inefficient hospitals in year 2007 to efficient hospitals in year 2008 by

SE scores. The pattern of scale inefficiency of changed from a decreasing return to scale (drs) pattern in year 2007 to scale efficiency in year 2008.

Table 4-4 Data of technical efficiency scores of input-orientated measurement DEA

Hospitals No. (DMU)		TECRSi		TEVRSi		SEi		Pattern of scale inefficiency	
2007	2008	2007	2008	2007	2008	2007	2008	2007	2008
1	26	1	0.951	1	1	1	0.951	-	irs
2	27	1	1	1	1	1	1	-	-
3	28	1	1	1	1	1	1	-	-
4	29	1	1	1	1	1	1	-	-
5	30	1	1	1	1	1	1	-	-
6	31	0.889	0.901	1	1	0.889	0.901	irs	irs
7	32	0.945	1	1	1	0.945	1	drs	-
8	33	1	1	1	1	1	1	-	-
9	34	0.977	0.915	0.985	0.926	0.992	0.988	irs	irs
10	35	1	1	1	1	1	1	-	-
11	36	1	1	1	1	1	1	-	-
12	37	1	1	1	1	1	1	-	-
13	38	1	1	1	1	1	1	-	-
14	39	0.887	1	0.989	1	0.896	1	irs	-
15	40	0.85	0.908	0.854	0.908	0.996	1	drs	-
16	41	0.896	0.912	0.966	0.982	0.927	0.929	irs	irs
17	42	1	1	1	1	1	1	-	-
18	43	0.905	1	0.947	1	0.955	1	irs	-
19	44	0.851	0.858	0.942	0.954	0.903	0.899	irs	irs
20	45	1	1	1	1	1	1	-	-
21	46	0.877	1	0.903	1	0.971	1	irs	-
22	47	0.81	1	0.811	1	0.999	1	drs	-
23	48	1	1	1	1	1	1	-	-
24	49	0.855	0.922	0.994	0.993	0.86	0.929	irs	irs
25	50	0.943	1	1	1	0.943	1	irs	-

Output-orientated measurement DEA; there were 12 from 25 regional hospitals which had all three efficiency scores (TECRS, TEVRS and SE scores equal to 1) such as hospital number 2, 3, 4, 5, 8, 10, 11, 12, 13, 17, 20, and 23 as Table 4-5 below. The results were the same as input-orientated measurement DEA. There were 5 from 25 regional hospitals which had all three inefficiency scores (TECRS, TEVRS and SE scores less than 1) such as hospital number 9, 15, 16, 19 and 24. The pattern of scale inefficiency in this group had three types; 1) an increasing return to scale (irs) pattern in both years such as hospital number 16, 19 and 24, 2) a decreasing return to scale (drs) pattern in both years such as hospital number 15 and 3) the pattern of scale inefficiency changed from an increasing return to scale (irs) in year 2007 to a decreasing return to scale (drs) in year 2008 such as hospital number 9. These results were different from input-orientated measurement DEA because 1) a hospital number 15 changed from scale efficiency in year 2008 of input-orientated measurement DEA to scale inefficiency in year 2008 of output-orientated measurement DEA and 2) a hospital number 9 changed from an increasing return to scale (irs) in year 2008 of input-orientated measurement DEA to a decreasing return to scale (drs) pattern in year 2008 of output-orientated measurement DEA. There were 4 from 25 regional hospitals which improved their all three efficiency scores (TECRS, TEVRS and SE scores changed from the inefficiency scores to efficiency scores) such as hospital number 14, 18, 21 and 22. There were three hospitals which the pattern of scale inefficiency improved from increasing return to scale (irs) pattern to scale efficiency (hospital number 14, 18, and 21) and only one hospital which improved from a decreasing return to scale (drs) pattern to scale efficiency (hospital number 22). The results were the same as input-orientated measurement DEA.

There were two hospitals which were efficient in TEVRS in both years (TEVRS scores equaled 1 in year 2007-2008) but improved from inefficient hospitals in year 2007 to efficient hospitals in year 2008 by TECRS and SE scores such as hospital number 7 and 25. The pattern of scale inefficiency of hospital number 7 changed from a decreasing return to scale (drs) pattern in year 2007 to scale efficiency in year 2008; however, the pattern of scale inefficiency of hospital number 25 changed from an increasing return to scale (irs) pattern in year 2007 to scale efficiency in year 2008. The results were the same as input-orientated measurement DEA.

Hospital number 1 was efficient in TEVRS in both years (TEVRS scores equaled 1 in year 2007-2008) but reduced from efficient hospitals in year 2007 to inefficient hospitals in year 2008 by TECRS and SE scores. The pattern of scale inefficiency of hospital number 1 changed from scale efficiency in year 2007 to an increasing return to scale (irs) pattern in year 2008. The results were the same as input-orientated measurement DEA.

Hospital number 6 was efficient in TEVRS in both years (TEVRS scores equaled 1 in year 2007-2008) but was inefficient hospitals in both years 2007-2008 by TECRS and SE scores. The pattern of scale inefficiency of hospital number 6 was an increasing return to scale (irs) pattern in both years. The results were not different as input-orientated measurement DEA.

Table 4-5 Data of technical efficiency scores of output-orientated measurement DEA

Hospitals No. (DMU)		TECRSo		TEVRSo		SEo		Pattern of scale inefficiency	
2007	2008	2007	2008	2007	2008	2007	2008	2007	2008
1	26	1	0.951	1	1	1	0.951	-	irs
2	27	1	1	1	1	1	1	-	-
3	28	1	1	1	1	1	1	-	-
4	29	1	1	1	1	1	1	-	-
5	30	1	1	1	1	1	1	-	-
6	31	0.889	0.901	1	1	0.889	0.901	irs	irs
7	32	0.945	1	1	1	0.945	1	drs	-
8	33	1	1	1	1	1	1	-	-
9	34	0.977	0.915	0.984	0.916	0.993	0.999	irs	drs
10	35	1	1	1	1	1	1	-	-
11	36	1	1	1	1	1	1	-	-
12	37	1	1	1	1	1	1	-	-
13	38	1	1	1	1	1	1	-	-
14	39	0.887	1	0.954	1	0.929	1	irs	-
15	40	0.85	0.908	0.862	0.923	0.987	0.984	drs	drs
16	41	0.896	0.912	0.946	0.974	0.947	0.937	irs	irs
17	42	1	1	1	1	1	1	-	-
18	43	0.905	1	0.925	1	0.978	1	irs	-
19	44	0.851	0.858	0.894	0.886	0.952	0.968	irs	irs
20	45	1	1	1	1	1	1	-	-
21	46	0.877	1	0.892	1	0.983	1	irs	-
22	47	0.81	1	0.817	1	0.991	1	drs	-
23	48	1	1	1	1	1	1	-	-
24	49	0.855	0.922	0.92	0.985	0.929	0.936	irs	irs
25	50	0.943	1	1	1	0.943	1	irs	-

The details of frequency of TECRSi, TEVRSi, and SEi scores of DEA, input-orientated measurement in year 2007-2008 were presented in Table B2, B3, and B3 respectively. The details of frequency of TECRSo, TEVRSo, and SEo scores of DEA, output orientated measurement in year 2007-2008 were presented in Table B5, B6, and B7 respectively.

Descriptive statistics of technical efficiency scores of both input- and output-orientated DEA

Descriptive statistics of technical efficiency scores of DEA, both input- and output-orientated showed the numbers, median, 25th percentiles, 75th percentile, minimum, maximum, and one-sample Kolmogorov-Smirnov test as Table 4-6 below. All descriptive statistics of technical efficiency scores were non-parametric statistics because all p-values of one-sample Kolmogorov-Smirnov test were less than 0.005. The mean, 75th percentile and maximum of all three types of efficiency scores were 1 and these scores were less than 1 in 25th percentiles and minimum. The TECRS scores of both input- and output-orientated DEA were the same value. The TEVRS and SE scores of both input- and output-orientated DEA were different in 25th percentiles and minimum, and the scores of output-orientated DEA were slightly higher than the scores of input-orientated DEA.

Table 4-6 Descriptive statistics of technical efficiency scores of both input- and output-orientated DEA

Descriptive statistics	Input-orientated DEA			Output-orientated DEA		
	TECRSi	TEVRSi	SEi	TECRSo	TEVRSo	SEo
Numbers	50	50	50	50	50	50
Median	1.000	1.000	1.000	1.000	1.000	1.000
Percentile 25th	0.911	0.992	0.954	0.911	0.982	0.976
Percentile 75th	1.000	1.000	1.000	1.000	1.000	1.000
Minimum	0.810	0.811	0.860	0.810	0.817	0.889
Maximum	1.000	1.000	1.000	1.000	1.000	1.000
One-sample K-S test - Asymp. sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000

Descriptive statistics of technical inefficiency scores and pattern of scale inefficiency of DEA, both input- and output-orientated measurement

There were the same frequencies of TECRS scores in all levels of scores of both input- and output-orientated DEA as Table 4-7 below. There were different in frequency of efficiency scores of SE of input-orientated (32 from 50 DMUs) and output-orientated DEA (31 from 50 DMUs) and some inefficiency scores of TEVRS and SE were different in frequency such as 85.0-89.9% and 95.0-99.9% but some inefficiency scores of TEVRS and SE were same in frequency as 80.0-84.9% among input- and output-orientated DEA.

Table 4-7 Technical efficiency scores classified by type of score and score levels of both input- & output-orientated DEA

Scores	Input-orientated DEA			Output-orientated DEA		
	TECRSi	TEVRSi	SEi	TECRSo	TEVRSo	SEo
100%	31	36	32	31	36	31
95.0-99.9%	2	7	7	2	4	10
90.0-94.9%	8	5	7	8	5	8
85.0-89.9%	8	1	4	8	4	1
80.0-84.9%	1	1	0	1	1	0
Total (DMU)	50	50	50	50	50	50

The patterns of scale inefficiency were different in frequency among input- and output-orientated DEA as Table 4-8 below. The frequencies of increasing returns to scale (irs) pattern were higher than the frequencies of decreasing return to scale (drs) pattern of both input- and output-orientated DEA; however, they were different in ratio.

Table 4-8 Frequency of pattern of scale inefficiency of both input- and output-orientated DEA

Items	Input-orientated DEA				Output-orientated DEA			
	Pattern of scale inefficiency				Pattern of scale inefficiency			
	-	irs	drs	total	-	irs	drs	total
Frequency	32	15	3	50	31	14	5	50
%	64.0	30.0	6.0	100.0	62.0	28.0	10.0	100.0

NOTE: drs = decreasing return to scale, irs = increasing return to scale

4.2.2 Results of both input- and output-orientated DEA analyzed with educational type

Regional hospitals in Thailand in year 2007-2008 can be classified to 2 groups; teaching and non-teaching hospitals, there were 20 non-teaching hospitals (DMUs) and 30 teaching hospitals (DMUs). Teaching hospitals can be divided into 2 subgroups as only undergraduate teaching hospitals and combined undergraduate and postgraduate teaching hospitals. So the educational types of regional hospitals in this study were classified to 3 types like Table 4-9 below.

Table 4-9 Subgroups of regional hospitals in Thailand by medical educational services

Education type	Description	Frequency	%
Type 1	Non-teaching	20	40.0
Type 2	Undergraduate teaching only	8	16.0
Type 3	Undergraduate + postgraduate teaching	22	44.0
	Total	50	100.0

NOTE: Non-teaching = type 1, Teaching hospital = type 2 + type 3

Overall technical efficiency analyzed with educational type

Overall technical efficiency analyzed about TECRS scores of both input- and output-orientated DEA and focused on educational types of regional hospitals. The results found that were not different as Table 4-10. In non-teaching hospitals, there were inefficient hospitals (55%) more than efficient hospitals (45%). But in group of teaching hospitals; both educational type 2 and type 3 hospitals, there were efficient hospitals (62.5%, 77.27%) more than inefficient hospitals (37.5%, 22.73% respectively). So teaching hospitals (type 2+3 were efficient = 73.33%) were more efficient than non-teaching hospitals (type 1 were efficient = 45%).

Table 4-10 Technical efficiency status of TECRS of both input- and output-orientated DEA

Education type	Technical efficiency status of TECRSi			Technical efficiency status of TECRSo		
	Efficient	Inefficient	Total	Efficient	Inefficient	Total
Type 1	9	11	20	9	11	20
(%)	(45)	(55)	(100)	(45)	(55)	(100)
Type 2	5	3	8	5	3	8
(%)	(62.5)	(37.5)	(100)	(62.5)	(37.5)	(100)
Type 3	17	5	22	17	5	22
(%)	(77.27)	(22.73)	(100)	(77.27)	(22.73)	(100)
Total	31	19	50	31	19	50
(%)	(62)	(38)	(100)	(62)	(38)	(100)
Type 2+3	22	8	30	22	8	30
(%)	(73.33)	(26.67)	(100)	(73.33)	(26.67)	(100)

In cases of inefficient hospitals which had TECRS scores less than 1. The results of both input- and output-orientated DEA found that were not different as Table 4-11 and 4-12. In group of non-teaching regional hospitals, most of them were in range 85.0-94.9% (72.73% of total inefficient DMUs). In addition, all teaching hospitals were in range 85.0-94.9%.

Table 4-11 TECRS scores of inefficient hospitals from input-orientated DEA

Education type	TECRSi scores of technical inefficient hospitals				
	80.0-84.9%	85.0-89.9%	90.0-94.9%	95.0-99.9%	Total
Type 1	1	4	4	2	11
Type 2	0	2	1	0	3
Type 3	0	2	3	0	5
Total	1	8	8	2	19

Table 4-12 TECRS scores of inefficient hospitals from output-orientated DEA

Education type	TECRSo scores of technical inefficient hospitals				
	80.0-84.9%	85.0-89.9%	90.0-94.9%	95.0-99.9%	Total
Type 1	1	4	4	2	11
Type 2	0	2	1	0	3
Type 3	0	2	3	0	5
Total	1	8	8	2	19

Pure technical efficiency analyzed with educational type

Pure technical efficiency analyzed about TEVRS scores of both input- and output-orientated DEA and focused on educational types of regional hospitals. The results found that were the same results as Table 4-13. Both non-teaching and teaching hospitals, there were efficient hospitals (65%, 76.67%) more than inefficient hospitals (35%, 23.33% respectively) and teaching hospitals (type 2+3 were efficient = 76.67%) were more efficient than non-teaching hospitals (type 1 were efficient = 65%). In group of teaching hospitals, educational type 3 hospitals (81.82%) were more efficient than educational type 2 hospitals (62.5%).

Table 4-13 Status of pure technical efficiency of both input- & output-orientated DEA

Education type	Technical efficiency status of TEVRSi			Technical efficiency status of TEVRSo		
	Efficient	Inefficient	Total	Efficient	Inefficient	Total
Type 1	13	7	20	13	7	20
(%)	(65)	(35)	(100)	(65)	(35)	(100)
Type 2	5	3	8	5	3	8
(%)	(62.5)	(37.5)	(100)	(62.5)	(37.5)	(100)
Type 3	18	4	22	18	4	22
(%)	(81.82)	(18.18)	(100)	(81.82)	(18.18)	(100)
Total	36	14	50	36	14	50
(%)	(72)	(28)	(100)	(72)	(28)	(100)
Type 2+3	23	7	30	23	7	30
(%)	(76.67)	(23.33)	(100)	(76.67)	(23.33)	(100)

In cases of inefficient hospitals which had TEVRS scores less than 1. The results of input- and output-orientated DEA found that were the different results as Table 4-14 and 4-15. Total frequencies of each educational type of inefficient hospitals from both input- and output-orientated DEA were same, but the detail of each level of inefficient hospitals was different.

Table 4-14 TEVRS scores of inefficient hospitals from input-orientated DEA

Education type	TEVRSi scores of technical inefficient hospitals				
	80.0-84.9%	85.0-89.9%	90.0-94.9%	95.0-99.9%	Total
Type 1	1	0	2	4	7
Type 2	0	1	1	1	3
Type 3	0	0	2	2	4
Total	1	1	5	7	14

Table 4-15 TEVRS scores of inefficient hospitals from output-orientated DEA

Education type	TEVRSo scores of technical inefficient hospitals				
	80.0-84.9%	85.0-89.9%	90.0-94.9%	95.0-99.9%	Total
Type 1	1	2	2	2	7
Type 2	0	1	1	1	3
Type 3	0	1	2	1	4
Total	1	4	5	4	14

Scale efficiency and the pattern of scale inefficiencies analyzed with educational type

1) **Scale efficiency**

Scale efficiency analyzed about SE scores of both input- and output-orientated DEA and focused on educational types of regional hospitals. The results found that some results were same and some results were different as Table 4-16 and 4-17.

- For the same results of both input- and output-orientated DEA. In group of non-teaching hospitals, there were inefficient hospitals (55%) more than efficient hospitals (45%). But in group of teaching hospitals; both educational type 2 and type 3 hospitals, there were efficient hospitals (75% and 77.27% for input-orientated, 62.5% and 77.27% for output-orientated) more than inefficient hospitals (25% and 22.73% for input-orientated, 37.5% and 22.73% for output-orientated respectively). So teaching hospitals (76.67% for input-orientated, 73.33% for output-orientated) were more efficient than non-teaching hospitals (45% for both input- and output-orientated).
- For the different results of both input- and output-orientated DEA. There were different in detail of frequencies of only educational type 2 hospitals.

2) **The pattern of scale inefficiencies**

There are two patterns of scale inefficiencies that are increasing return to scale (irs) and decreasing return to scale (drs). The results found that there were the increasing returns to scale of inefficient hospitals more than the decreasing returns to scale of inefficient hospitals in educational type 1 (irs:drs = 10:1 for input-orientated, irs:drs = 9:2 for output-orientated) and type 3 (irs:drs = 4:1 for both input- and output-orientated) hospitals of both input- and output-orientated DEA, but they were different in details of frequencies of the pattern of scale inefficiencies as Table 4-16 and 4-17. In educational type 2 hospitals of input-orientated DEA, the frequency of increasing return to scale was as same as the frequency of decreasing return to scale (irs = drs = 1); however, in educational type 2 hospitals of output-orientated DEA, the frequencies of decreasing return to scale (drs = 2) were more than the frequencies of increasing return to scale (irs = 1).

Table 4-16 Status of scale efficiency and pattern of scale inefficiency of input-orientated DEA

Education type	Status of scale efficiency of input-orientated DEA					
	Efficient	Inefficient	Total	Pattern of scale inefficiency		
				DRSi	IRSi	Total
Type 1	9	11	20	1	10	11
(%)	(45)	(55)	(100)	(9.09)	(90.91)	(100)
Type 2	6	2	8	1	1	2
(%)	(75)	(25)	(100)	(50)	(50)	(100)
Type 3	17	5	22	1	4	5
(%)	(77.27)	(22.73)	(100)	(20)	(80)	(100)
Total	32	18	50	3	15	18
(%)	(64)	(36)	(100)	(16.67)	(83.33)	(100)
Type 2+3	23	7	30	2	5	7
(%)	(76.67)	(23.33)	(100)	(28.57)	(71.43)	(100)

Table 4-17 Status of scale efficiency and pattern of scale inefficiency of output-orientated DEA

Education type	Status of scale efficiency of output-orientated DEA					
	Efficient	Inefficient	Total	Pattern of scale inefficiency		
				DRSo	IRSo	Total
Type 1	9	11	20	2	9	11
(%)	(45)	(55)	(100)	(18.18)	(81.82)	(100)
Type 2	5	3	8	2	1	3
(%)	(62.5)	(37.5)	(100)	(66.67)	(33.33)	(100)
Type 3	17	5	22	1	4	5
(%)	(77.27)	(22.73)	(100)	(20)	(80)	(100)
Total	31	19	50	5	14	19
(%)	(62)	(38)	(100)	(26.32)	(73.68)	(100)
Type 2+3	22	8	30	3	5	8
(%)	(73.33)	(26.67)	(100)	(37.5)	(62.5)	(100)

In cases of inefficient hospitals which had SE scores less than 1. The results of both input- and output-orientated DEA found that were near totally different results as Table 4-18 and 4-19. The frequencies of both educational type 1 and type 2 hospitals of inefficient hospitals from both input- and output-orientated DEA were different but the frequencies of educational type 3 hospitals from both input- and output-orientated DEA were same.

Table 4-18 Scale efficiency scores of inefficient hospitals from input-orientated DEA

Education type	SEi scores of technical inefficient hospitals				
	80.0-84.9%	85.0-89.9%	90.0-94.9%	95.0-99.9%	Total
Type 1	0	3	4	4	11
Type 2	0	1	0	1	2
Type 3	0	0	3	2	5
Total	0	4	7	7	18

Table 4-19 Scale efficiency scores of inefficient hospitals from output-orientated DEA

Education type	SEo scores of technical inefficient hospitals				
	80.0-84.9%	85.0-89.9%	90.0-94.9%	95.0-99.9%	Total
Type 1	0	1	4	6	11
Type 2	0	0	1	2	3
Type 3	0	0	3	2	5
Total	0	1	8	10	19

4.2.3 Comparison of efficiency scores and educational type by ranking

The results of efficiency scores and education type of both types of DEA were compared by ranking in order and found that only TECRS scores were not different in both types of TECRSi, TECRSo scores as Table B8. All efficient DMUs of both types of TEVRSi, TEVRSo scores were same but most of inefficient DMUs of both types of scores were different except the last two inefficient DMUs (the 15th DMU was in educational type 2 and the 22th DMU was in educational type 1) were same as Table B9. Most of efficient DMUs of both types of SEi and SEo scores were same except one DMU (the 40th DMU) which changed from efficient DMU of SEi scores to inefficient DMU of SEo scores. However, all of inefficient DMUs of both types of SEi and SEo scores were totally different in sequence, pattern of scale inefficiency and education type as Table B10.

4.3 Descriptive analysis of explanatory variables of regression analysis

Simple linear regression model (ordinary least square estimation) was used to provide more details about the factors affecting on the technical efficiency scores of regional hospitals (determinants of hospital efficiency). Technical efficiency under variable return to scale assumption (TEVRS) and scale efficiency (SE) from DEA were used as dependent variables combining with twelve independent variables to calculate the magnitude and direction of their relation. There were four equations of ordinary least square estimation for both input- and output-orientated DEA using EViews as below.

Input-orientated:

$$VRSi=c(1)+c(2)*BP+c(3)*P+c(4)*P^2+c(5)*NP+c(6)*OPP+c(7)*IPS+c(8)*RPS \quad (4\text{-}1)$$

$$SEi=c(1)+c(2)*OP+c(3)*IDRGP+c(4)*MPS+c(5)*U_j+c(6)*HA_j \quad (4\text{-}2)$$

Output-orientated:

$$VRSo=c(1)+c(2)*BP+c(3)*P+c(4)*P^2+c(5)*NP+c(6)*OPP+c(7)*IPS+c(8)*RPS \quad (4\text{-}3)$$

$$SEo=c(1)+c(2)*OP+c(3)*IDRGP+c(4)*MPS+c(5)*U_j+c(6)*HA_j \quad (4\text{-}4)$$

There were seven explanatory variables of TEVRS in equations 1 and 3 for both input- and output-orientated DEA. The explanatory variables of TEVRS were beds-physician ratio (BP), numbers of physicians (P), numbers of physicians in form of square (P^2), nurses-physician ratio (NP), other personnel-physician ratio (OPP), trained interns-physician staff ratio (IPS) and graduated residents-physician staff ratio (RPS).

There were five explanatory variables of SE in equations 2 and 4 for both input- and output-orientated DEA. The explanatory variables of SE were out-patient visits per physician (OP), in-patient visits adjusted with relative weight of DRG per physician (IDRGP), graduated medical student per physician staff (MPS), and two dummy variables; location of regional hospital staying near University hospital (U_j) and quality of health care service meeting Thailand Hospital Accreditation criteria (HA_j).

Descriptive statistics of five normal-distributional explanatory variables of TEVRS scores showed the numbers, mean, standard deviation, minimum, maximum and one-sample Kolmogorov-Smirnov test as presented in Table 4-20. They were BP, P, NP, OPP and IPS. All of them had p-values of one-sample Kolmogorov-Smirnov test were more than 0.005 (normal distribution).

Table 4-20 Descriptive statistics of explanatory variables of TEVRS scores

Descriptive statistics	BP	P	NP	OPP	IPS
Numbers	50	50	50	50	50
Mean	5.53	139.90	5.04	8.35	0.22
Standard deviation	1.52	58.61	1.51	2.37	0.07
Minimum	2.94	54	2.74	3.89	0.11
Maximum	9.35	275	10.65	14.80	0.43
One-sample K-S test - Asymp. sig. (2-tailed)	0.928	0.486	0.405	0.790	0.374

Descriptive statistics of two normal-distributional explanatory variables of SE scores showed the numbers, mean, standard deviation, minimum, maximum and one-sample Kolmogorov-Smirnov test as presented in Table 4-21. They were OP and IDRGP. Both of them had p-values of one-sample Kolmogorov-Smirnov test more than 0.005 (normal distribution).

Table 4-21 Descriptive statistics of explanatory variables of SE scores

Descriptive statistics	OP	IDRGP
Numbers	50	50
Mean	4120.19	496.44
Standard deviation	1056.59	131.86
Minimum	2232.23	212.16
Maximum	6443.75	854.20
One-sample K-S test - Asymp. sig. (2-tailed)	0.720	0.999

Descriptive statistics of three not normal-distributional explanatory variables of TEVRS and SE scores showed the numbers, mean, standard deviation, minimum, maximum and one-sample Kolmogorov-Smirnov test as presented in Table 4-22. All of them had p-values of one-sample Kolmogorov-Smirnov test less than 0.005 (not normal distribution). There were two explanatory variables of TEVRS which were P^2 and RPS, and one explanatory variable of SE which was MPS.

Table 4-22 Descriptive statistics of explanatory variables of TEVRS and SE scores (not normal distribution)

Descriptive statistics	MPS	RPS	P^2
Numbers	50	50	50
Median	0.0150	0.0000	15626.00
Percentile 25^{th}	0.0000	0.0000	8557.00
Percentile 75^{th}	0.1878	0.0249	29941.00
Minimum	0.00	0.00	2916
Maximum	0.54	0.15	75625
One-sample K-S test - Asymp. sig. (2-tailed)	0.001	0.000	0.040

There were two dummy variables in this study; the first was the location of regional hospital staying near University hospital (U_j) and the second was the quality of health care service meeting Thailand Hospital Accreditation criteria (HA_j). The frequencies of these dummy variables were presented in Table 4-23. From Table C4 showed the details of both dummy variables. Only four from 25 regional hospitals stayed near university hospital. There were only 5 regional hospital meeting hospital accreditation criteria in 2007 and 10 regional hospital meeting hospital accreditation criteria in 2008.

Table 4-23 Frequency of dummy variables

Items	Dummy variables					
	U_j			HA_j		
	U_0	U_1	Total	HA_0	HA_1	Total
Frequency	42	8	50	15	35	50
%	84.0	16.0	100.0	30.0	70.0	100.0

NOTE: U_0 = near university hospital, U_1 = not near university hospital
HA_0 = pass hospital accreditation, HA_1 = not pass hospital accreditation

4.4 The results of regression analyses from both input- and output-orientated DEA

Several regression models (ordinary least square estimation and tobit estimation) were run using Eviews program and compared for goodness of fits, only the best fits and the most simple models were presented here as Table 4-24 to 4-27 for both input- and output-orientated DEA. The results of the details were presented as Appendices in Table D1 to D4 and the other tested regression models (alternative models) were provided in Table E5 to E36.

4.4.1 Results of regression analyses

Results of regression analyses from input-orientated DEA

For input-orientated DEA, the best fit estimated equation for TEVRSi scores was shown as below.

$$\text{TEVRSi scores} = 1.193648 - 0.027043BP - 0.001455P + 3.26E\text{-}06P^2 + 0.018173NP - 0.008207OPP + 0.182930IPS + 0.222389RPS \qquad (4\text{-}5)$$

Most explanatory variables of TEVRSi scores significantly correlated to TEVRSi scores but only RPS insignificantly correlated to TEVRSi scores because p-value of RPS was more than 0.05 (0.1825) as Table 4-24 below. There were three explanatory variables which reversely correlated to TEVRSi scores because their coefficients had negative sign such as BP, P and OPP. The remaining explanatory variables directly correlated to TEVRSi scores.

R-squared value (R^2) of this estimated equation was slightly low (R^2 = 0.380479) because the selected explanatory variables may be not the good explanatory variables for this dependent variable (TEVRSi scores). From running regression, the result revealed the probability (F-statistic) = 0.003432 meaning this equation was linear statistical model. For the detection of problem of autocorrelation, this study used panel data (only two years, not time series data) and Durbin-Watson stat showed a good value (1.915414); this number was near to two that accepted the null hypothesis which had no autocorrelation problem. For the detection of problem of multicollinearity, the result did not show high output of R-squared and low output t-statistic. In addition, Eviews' estimation checked for correlation among all explanatory variables of TEVRSi scores as Table F1 shown only P and P^2 closely correlated together (a value was close to 1) and some pairs of explanatory variables slightly correlated together such as BP and NP, BP and P, and OPP and NP. For the detection of problem of heteroscedasticity, the results of Residual test/ White's General Heteroscedasticity Test; both including and not including White Cross Term, revealed that p-values of F-statistic and Obs*R-squared were more than 0.05, but Scaled explained SS were less than 0.05 as Table F3 and F4. So this model had no problem of heteroscedasticity.

It can explain that if beds-physician ratio (BP) decreased one unit, TEVRSi scores tended to increase 0.027043 units, giving other things were constant. If the numbers of physicians (P) decreased one unit, TEVRSi scores tended to increase 0.001455 units, giving other things were constant. If the numbers of physicians in form of square (P^2) increased one unit, TEVRSi scores tended to increase 3.26E-06 units (very low, insignificant), giving other things were constant. If nurses-physician ratio (NP) increased one unit, TEVRSi scores tended to increase 0.018173 units, giving other things were constant. If other personnel-physician ratio (OPP) decreased one unit, TEVRSi scores tended to increase 0.008207 units, giving other things were constant. If trained interns-physician staff ratio (IPS) increased one unit, TEVRSi scores tended to increase 0.182930 units, giving other things were constant. And the most influential explanatory variable of TEVRSi scores was a trained interns-physician staff ratio (IPS) because its coefficient had the highest value among significant explanatory variables.

Table 4-24 Eviews' OLS estimation for TEVRS of input-orientated DEA

Explanatory variables	Parameters	Coefficient	t-statistic	p-value
Constant	C(1)	1.193648	17.22426	0.0000
BP	C(2)	-0.027043	-3.632140	0.0008
P	C(3)	-0.001455	-2.737622	0.0090
P^2	C(4)	3.26E-06	2.221315	0.0318
NP	C(5)	0.018173	2.310698	0.0258
OPP	C(6)	-0.008207	-2.354063	0.0233
IPS	C(7)	0.182930	2.534301	0.0151
RPS	C(8)	0.222389	1.355429	0.1825

N = 50, R^2 = 0.380479,
Probability (F-statistic) = 0.003432, Durbin-Watson stat = 1.915414

For input-orientated DEA, the best fit estimated equation for SEi scores was shown as below.

$$\text{SEi scores} = 0.897460 - 4.34\text{E-}06\text{OP} + 0.000152\text{IDRGP} + 0.044599\text{MPS} + 0.036886U_j + 0.016369HA_j \quad (4\text{-}6)$$

Most explanatory variables of SEi scores insignificantly correlated to SEi scores, only IDRGP and Ui significantly correlated to SEi scores because their p-value were less than 0.05 as Table 4-25 below. There was one explanatory variable; OP, which reversely correlated to SEi scores because its coefficient had negative sign. The remaining explanatory variables directly correlated to SEi scores.

R-squared value (R^2) of this estimated equation was slightly low (R^2 = 0.230247, less than TEVRSi scores) because the selected explanatory variables may be not the good explanatory variables for this dependent variable (SEi scores). From running regression, the result revealed the probability (F-statistic) = 0.036283 meaning this equation was linear statistical model. For the detection of problem of autocorrelation, this study used panel data (only two years, not time series data) and

Durbin-Watson stat showed a good value (2.039775); this number was very near to two that accepted the null hypothesis which had no autocorrelation problem. For the detection of problem of multicollinearity, the result did not show high output of R-squared and low output t-statistic. In addition, Eviews' estimation checked for correlation among all explanatory variables of SEi scores as Table F2 shown no pairs of explanatory variables closely correlated together (a value was not close to 1). For the detection of problem of heteroscedasticity, the results of Residual test/ White's General Heteroscedasticity Test; both including and not including White Cross Term, revealed that p-values of F-statistic, Obs*R-squared and Scaled explained SS were more than 0.05 as Table F5 and F6. So this model had no problem of heteroscedasticity.

It can explain that if the in-patient visits adjusted with relative weight of DRG per physician (IDRGP) increased one unit, SEi scores tended to increase 0.000152 units, giving other things were constant. If the location of regional hospital staying near University hospital (U_1), SEi scores tended to increase 0.036886 units comparing with regional hospital not staying near University hospital (U_0), giving other things were constant. And the most influential explanatory variable of SEi scores was the location of regional hospital staying near University hospital (U_j) because its coefficient had the highest value among significant explanatory variables.

Table 4-25 Eviews' OLS estimation for SE of input-orientated DEA

Explanatory variables	Parameters	Coefficient	t-statistic	p-value
Constant	C(1)	0.897460	23.69902	0.0000
OP	C(2)	-4.34E-06	-0.743358	0.4612
IDRGP	C(3)	0.000152	3.013658	0.0043
MPS	C(4)	0.044599	1.023312	0.3118
U_j	C(5)	0.036886	2.098925	0.0416
HA_j	C(6)	0.016369	1.364226	0.1794
N = 50,		R^2 = 0.230247,		
Probability (F-statistic) = 0.036283, Durbin-Watson stat = 2.039775				

Results of regression analyses from output-orientated DEA

For output-orientated DEA, the best fit estimated equation for TEVRSo scores was shown as below.

$$\begin{aligned}\text{TEVRSo scores} = {} & 1.136643 - 0.029290BP - 0.001107P + 2.48E\text{-}06P^2 + 0.023639NP \\ & - 0.008336OPP + 0.208326IPS + 0.266873RPS \qquad (4\text{-}7)\end{aligned}$$

Most explanatory variables of TEVRSo scores significantly correlated to TEVRSo scores but P, P^2 and RPS insignificantly correlated to TEVRSo scores because their p-values were more than 0.05 as Table 4-26 below. There were three explanatory variables which reversely correlated to TEVRSo scores because their coefficients had negative sign such as BP, P and OPP. The remaining explanatory variables directly correlated to TEVRSo scores.

R-squared value (R^2) of this estimated equation was slightly low (R^2 = 0.372030, a little bit less than TEVRSi scores) because the selected explanatory variables may be not the good explanatory variables for this dependent variable (TEVRSo scores). From running regression, the result revealed the probability (F-statistic) = 0.004342 meaning this equation was linear statistical model. For the detection of problem of autocorrelation, this study used panel data (only two years, not time series data) and Durbin-Watson stat showed a good value (2.075374); this number was near to two that accepted the null hypothesis which had no autocorrelation problem. For the detection of problem of multicollinearity, the result did not show high output of R-squared and low output t-statistic. In addition, Eviews' estimation checked for correlation among all explanatory variables of TEVRSo scores as Table F1 (the same as TEVRSi scores) shown that only P and P^2 closely correlated together (a value was close to 1) and some pairs of explanatory variables slightly correlated together such as BP and NP, BP and P, and OPP and NP. For the detection of problem of heteroscedasticity, the results of Residual test/ White's General Heteroscedasticity Test; both including and not including White Cross Term, revealed that p-values of F-statistic, Obs*R-squared and Scaled explained SS were more than 0.05 as Table F7 and F8. Except only not including White Cross Term, Scaled explained SS were less than 0.05 as Table E8. So this model had no problem of heteroscedasticity.

It can explain that if beds-physician ratio (BP) decreased one unit, TEVRSo scores tended to increase 0.029290 units, giving other things were constant. If nurses-physician ratio (NP) increased one unit, TEVRSo scores tended to increase 0.023639 units, giving other things were constant. If other personnel-physician ratio (OPP) decreased one unit, TEVRSo scores tended to increase 0.008336 units, giving other things were constant. If trained interns-physician staff ratio (IPS) increased one unit, TEVRSo scores tended to increase 0.208326 units, giving other things were constant. And the most influential explanatory variable of TEVRSo scores was a trained interns-physician staff ratio (IPS) because its coefficient had the highest value among significant explanatory variables like TEVRSo scores but it was a little bit more.

Table 4-26 Eviews' OLS estimation for TEVRS of output-orientated DEA

Explanatory variables	Parameters	Coefficient	t-statistic	p-value
Constant	C(1)	1.136643	14.63952	0.0000
BP	C(2)	-0.029290	-3.511322	0.0011
P	C(3)	-0.001107	-1.859346	0.0700
P^2	C(4)	2.48E-06	1.511116	0.1382
NP	C(5)	0.023639	2.682740	0.0104
OPP	C(6)	-0.008336	-2.134202	0.0387
IPS	C(7)	0.208326	2.576048	0.0136
RPS	C(8)	0.266873	1.451801	0.1540

N = 50, R^2 = 0.372030,
Probability (F-statistic) = 0.004342, Durbin-Watson stat = 2.075374

For output-orientated DEA, the best fit estimated equation for SEo scores was shown as below.

$$\text{SEo scores} = 0.928444 - 4.39\text{E-}06\text{OP} + 0.000110\text{IDRGP} + 0.033221\text{MPS} + 0.025174\text{U}_j + 0.014607\text{HA}_j \quad (4\text{-}8)$$

Most explanatory variables of SEo scores insignificantly correlated to SEo scores, only IDRGP significantly correlated to SEo scores because its p-value was less than 0.05 (0.0059) as Table 4-27 below. There was one explanatory variable; OP, which reversely correlated to SEo scores because its coefficient had negative sign. The remaining explanatory variables directly correlated to SEo scores.

R-squared value (R^2) of this estimated equation was slightly low (R^2 = 0.231005, less than TEVRSo scores) because the selected explanatory variables may be not the good explanatory variables for this dependent variable (SEo scores). From running regression, the result revealed the probability (F-statistic) = 0.035650 meaning this equation was linear statistical model. For the detection of problem of autocorrelation, this study used panel data (only two years, not time series data) and Durbin-Watson stat showed a good value (1.826792); this number was near to two that accepted the null hypothesis which had no autocorrelation problem. For the detection of problem of multicollinearity, the result did not show high output of R-squared and low output t-statistic. In addition, Eviews' estimation checked for correlation among all explanatory variables of SEo scores as Table F2 shown no pairs of explanatory variables closely correlated together (a value was not close to 1). For the detection of problem of heteroscedasticity, the results of Residual test/ White's General Heteroscedasticity Test; both including and not including White Cross Term, revealed that p-values of F-statistic, Obs*R-squared and Scaled explained SS were more than 0.05 as Table F9 and F10. Except only not including White Cross Term, Scaled explained SS were less than 0.05 as Table E10. So this model had no problem of heteroscedasticity.

It can explain that if the in-patient visits adjusted with relative weight of DRG per physician (IDRGP) increased one unit, SEo scores tended to increase 0.000110 units, giving other things were constant. And the most influential explanatory variables of SEo scores was the in-patient visits adjusted with relative weight of DRG per physician (IDRGP) because it was only one significant explanatory variable.

Table 4-27 Eviews' OLS estimation for SE of output-orientated DEA

Explanatory variables	Parameters	Coefficient	t-statistic	p-value
Constant	C(1)	0.928444	32.66435	0.0000
OP	C(2)	-4.39E-06	-1.000848	0.3224
IDRGP	C(3)	0.000110	2.896914	0.0059
MPS	C(4)	0.033221	1.015537	0.3154
U_j	C(5)	0.025174	1.908459	0.0629
HA_j	C(6)	0.014607	1.622005	0.1119

N = 50, R^2 = 0.231005,
Probability (F-statistic) = 0.035650, Durbin-Watson stat = 1.826792

4.4.2 Other methods of regression analyses

Several regression models were run using Eviews program and compared for goodness of fits to search the best regression model. Because the technical efficiency scores; TEVRS scores and SE scores as dependent variables of regression analyses had very narrow range of value; 0.811-1.000 for VRSi, 0.817-1.000 for VRSo, 0.860-1.000 for SEi and 0.889-1.000 for SEo as Table 4-6. And most of these technical efficiency scores were efficient (TEVRS or SE scores = 1.000); there were 36 efficient DMUs from 50 DMUs for VRSi and VRSo, there were 32 efficient DMUs from 50 DMUs for SEi, and there were 31 efficient DMUs from 50 DMUs for SEo as Table 4-7. If technical efficiency scores can be expanded, the results of regression analyses should be better. So several forms of dependent variables of regression analyses were applied using Eviews' OLS estimation and Eviews' Tobit estimation such as

1. Eviews' OLS estimation for TEVRS and SE scores by changing dependent variables in exponential form of TEVRS and SE scores and the details of results were presented in Table G1-G4.
2. Eviews' OLS estimation for TEVRS and SE scores by changing dependent variables in semi-log form (ln) of TEVRS and SE scores and the details of results were presented in Table G5-G8.
3. Eviews' OLS estimation for TEVRS and SE scores by changing dependent variables in reciprocal form of TEVRS and SE scores and the details of results were presented in Table G9-G12.
4. Eviews' Tobit estimation for TEVRS and SE scores (both truncated and not truncated sample); by changing dependent variables in reciprocal form of TEVRS and SE scores and the details of results were presented in Table G13-G20.

Most results of other methods of regression analyses were the same as the results of Eviews' OLS estimation for TEVRS and SE scores by not changing dependent variables (original forms) except:

1. The signs of coefficients of explanatory variables in reciprocal form and Tobit estimation were reversely from original, exponential and semi-log forms of dependent variables.
2. Only Eviews' Tobit estimation for TEVRS and SE scores (both truncated and not truncated sample); by changing dependent variables in reciprocal form of TE scores in output-orientated DEA; the results of regression analyses looked better because they increased one significant explanatory variable in both results of TEVRS and SE scores as Table G17-G20. For TEVRS scores in output-orientated DEA; C(3) or coefficient of number of physicians (P) changed from insignificant value to significant value. For SE scores in output-orientated DEA; C(5) or coefficient of location of regional hospital staying near University hospital (U_j) changed from insignificant value to significant value. These were better for regression analyses of output-orientated DEA.

4.4.3 Relation between determinants

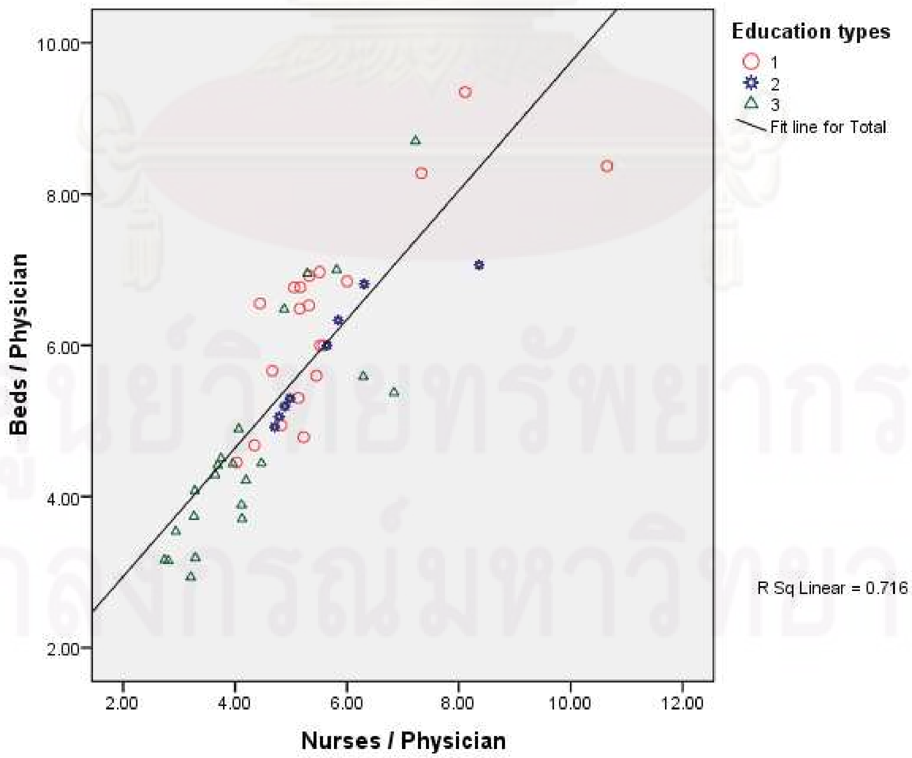
There were seven explanatory variables of TEVRS scores and there were five explanatory variables of SE scores. The relation of explanatory variables can be explored each pair of explanatory variables by using Eviews' estimation for checking the correlation among all explanatory variables in table presentation or/and in graph presentation.

Eviews' estimation checked for correlation among all explanatory variables of TEVRSi scores as Table F1 shown only P and P^2 closely correlated together (a value was close to 1) and some pairs of explanatory variables slightly correlated together such as BP and NP, BP and P, and OPP and NP. While Eviews' estimation checked for correlation among all explanatory variables of SEi scores and the results revealed as Table F2 shown no pairs of explanatory variables closely correlated together (a value was not close to 1).

Relation between resources

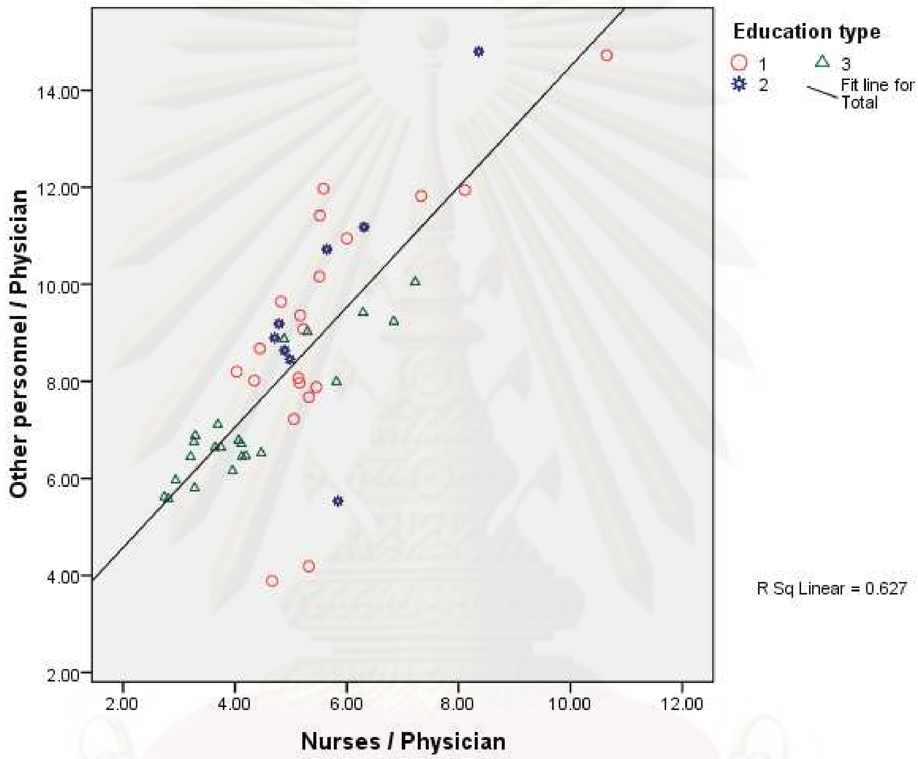
For graph analysis, the relation between beds per physician (BP) and nurses per physician (NP) was presented by graph as Figure 4-1 below and showed a linear relationship so if beds per physician increased, nurses per physician will increase too. In general, nurses are complementary to physicians but in some situations nurses can substitute to physicians for some jobs in health care services or/and medical education services. In educational type 3 hospitals, the physicians consumed beds and nurses less than both educational type 2 and type 1 hospitals because physician staffs in educational type 3 hospitals spent a lot of time to take care of complicated patients and teach both undergraduate and postgraduate level and most of their jobs required specialists and sub-specialist doctors so nurses can not substitute.

Figure 4-1 Relation between beds per physician and nurses per physician



The relation between other personnel per physician (OPP) and nurses per physician (NP) was presented by graph as Figure 4-2 below and showed a linear relationship so if other personnel per physician increased, nurses per physician will increase too. In general, other personnel are complementary to physicians and nurses so when hospital increases the numbers of physicians, it will increase the numbers of nurses and other personnel too. In educational type 3 hospitals, the physicians consumed human resources less than both educational type 2 and type 1 hospitals because of the complicate work in educational type 3 hospitals.

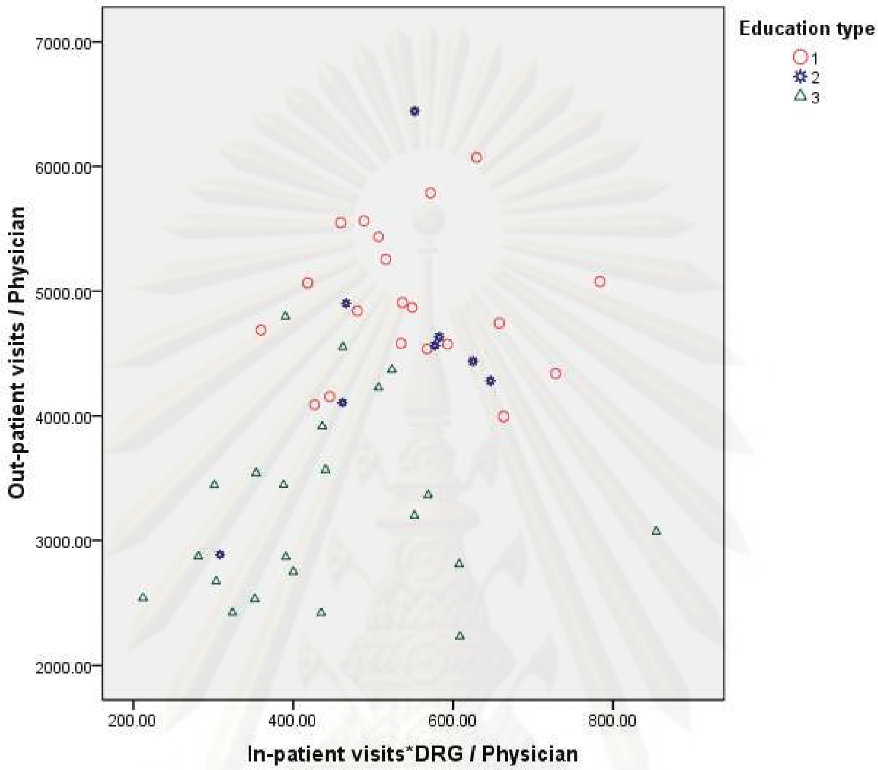
Figure 4-2 Relation between other personnel per physician and nurses per physician



Health care services

For health care services, the relation between out-patient visits per physician and in-patient visits per physician distributed like three groups classified by educational type as Figure 4-3 below. Teaching regional hospitals (both educational type 2 and type 3) can produce out-patient visits per physician and in-patient visits adjusted with relative weight of DRG per physician less than non-teaching regional hospitals (educational type 1). Among teaching hospitals, educational type 3 hospitals can produce out-patient visits per physician and in-patient visits adjusted with relative weight of DRG per physician (health care services) less than educational type 2 hospitals because of the more work load in educational type 3 hospitals.

Figure 4-3 Relation between out-patient visits per physician and in-patient visits*DRG per physician



- **Out-patient service**

The relation between out-patient visits per physician and beds per physician distributed like three groups classified by educational type as Figure 4-4 below and the relation between out-patient visits per physician and nurses per physician distributed like three groups classified by educational type as Figure 4-5 below. Teaching regional hospitals (both educational type 2 and type 3) can produce out-patient visits per physician less than non-teaching regional hospitals (educational type 1); in addition, teaching regional hospitals consumed resources (beds and nurses) less than non-teaching regional hospitals. Among teaching hospitals, educational type 3 hospitals can produce out-patient visits per physician less than educational type 2 hospitals; in addition, educational type 3 hospitals consumed resources (beds and nurses) less than educational type 2 hospitals, because of the more work load of physician staffs in educational type 3 hospitals.

Figure 4-4 Relation between out-patient visits per physician and beds per physician

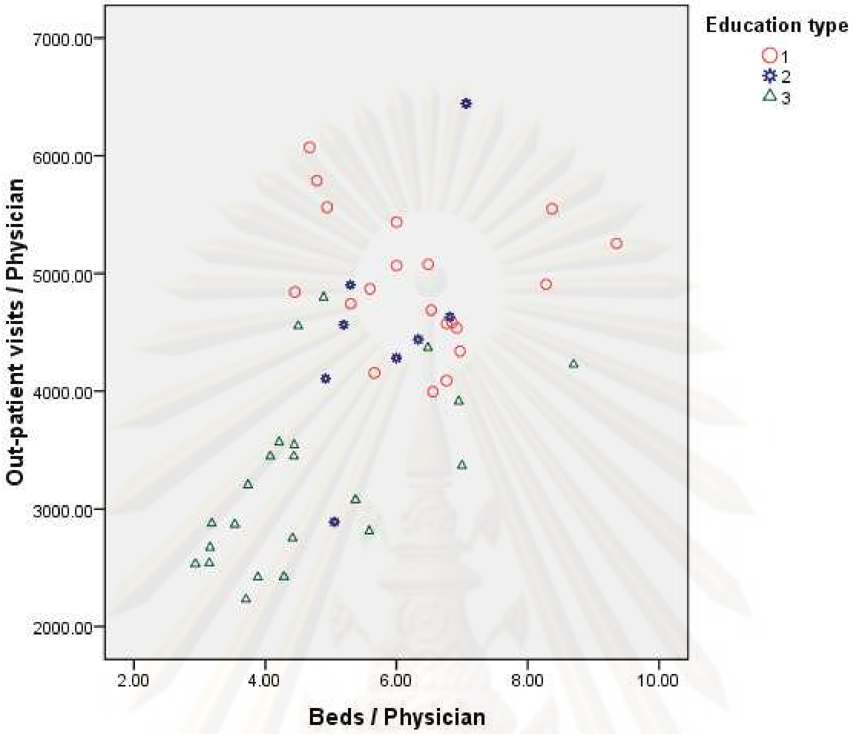
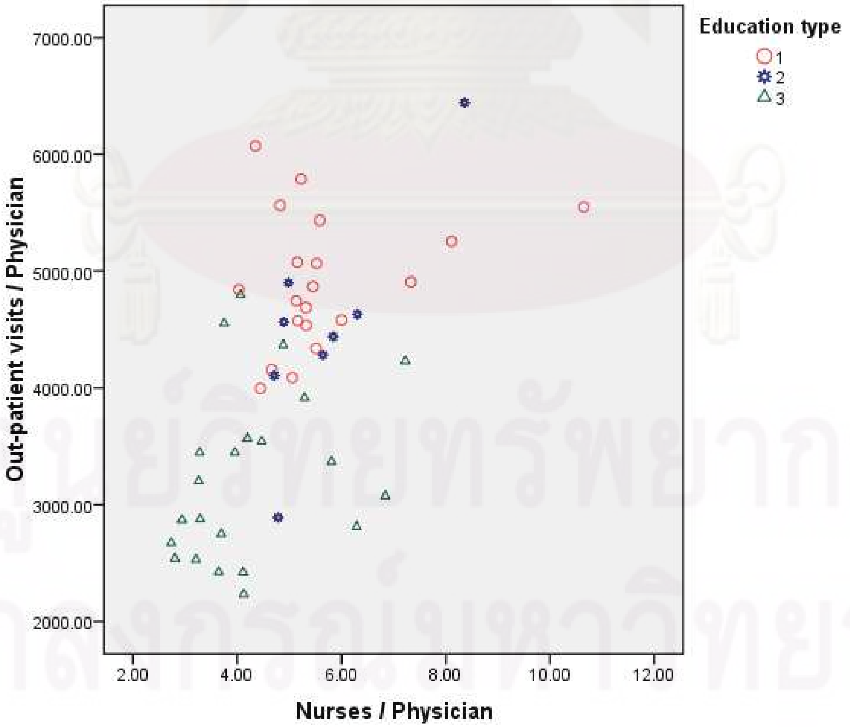
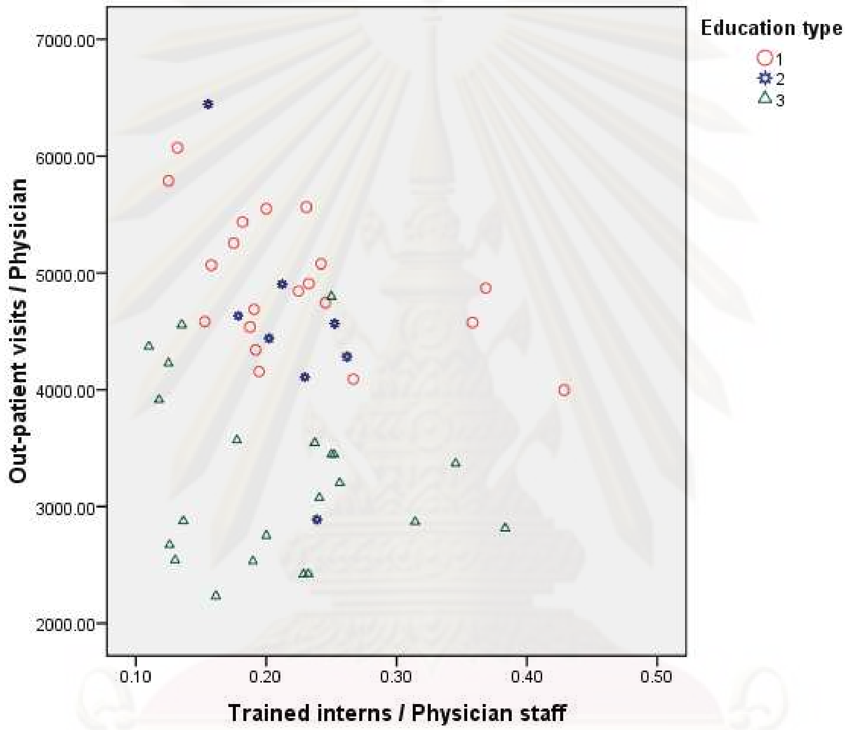


Figure 4-5 Relation between out-patient visits per physician and nurses per physician



The relation between out-patient visits per physician and trained interns per physician staff distributed like three groups classified by educational type as Figure 4-6 below. Teaching regional hospitals (both educational type 2 and type 3) can produce out-patient visits per physicians and trained interns per physician staff less than non-teaching regional hospitals (educational type 1). And among teaching hospitals, educational type 3 hospitals can produce out-patient visits per physicians and trained interns per physician staff less than educational type 2 hospitals. Because the more work load in educational type 3 hospitals, the physicians produced the lesser health care services as out-patient service or/and medical education services as trained interns.

Figure 4-6 Relation between out-patient visits per physician and trained interns per physician staff



However, the relation between out-patient visits per physician and graduated medical student per physician staff, and the relation between out-patient visits per physician and trained residents per physician staff did not definitely correlate together as Figure H1-H2.

- **In-patient service**

The relation between in-patient visits adjusted with relative weight of DRG per physician and beds per physician distributed like three groups classified by educational type as Figure 4-7 below and the relation between in-patient visits adjusted with relative weight of DRG per physician and nurses per physician distributed like three groups classified by educational type as Figure 4-8 below. But both educational type 2 and type 1 hospitals can not exactly discriminate. Educational type 3 hospitals can produce in-patient visits adjusted with relative weight of DRG per physician less than both educational type 2 and type 1 hospitals; in addition, educational type 3 hospitals consumed resources (beds and nurses) less than educational type 2 and type 1 hospitals because the more work load of physician staffs in educational type 3 hospitals.

Figure 4-7 Relation between in-patient visits*DRG per physician and beds per physician

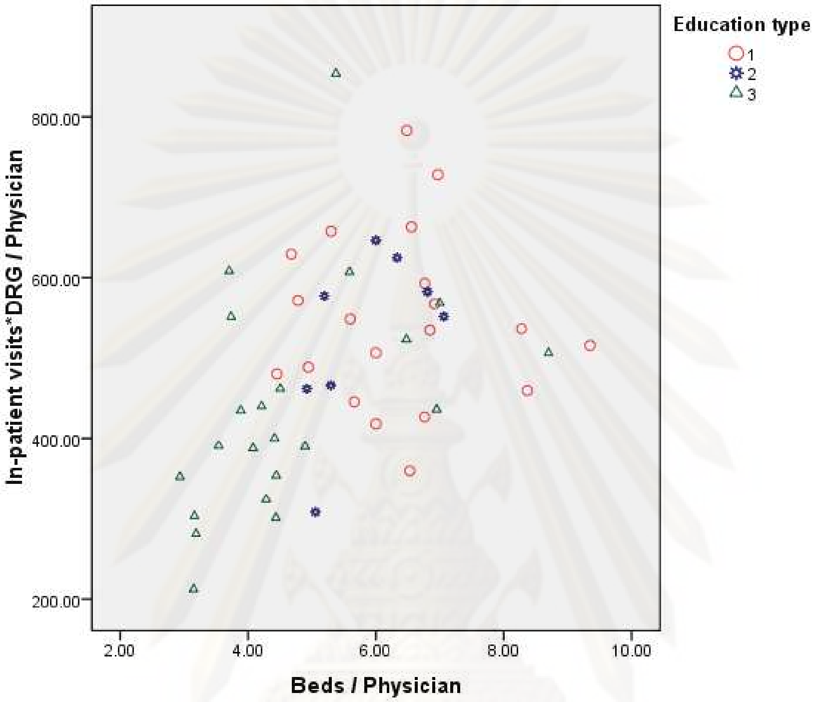
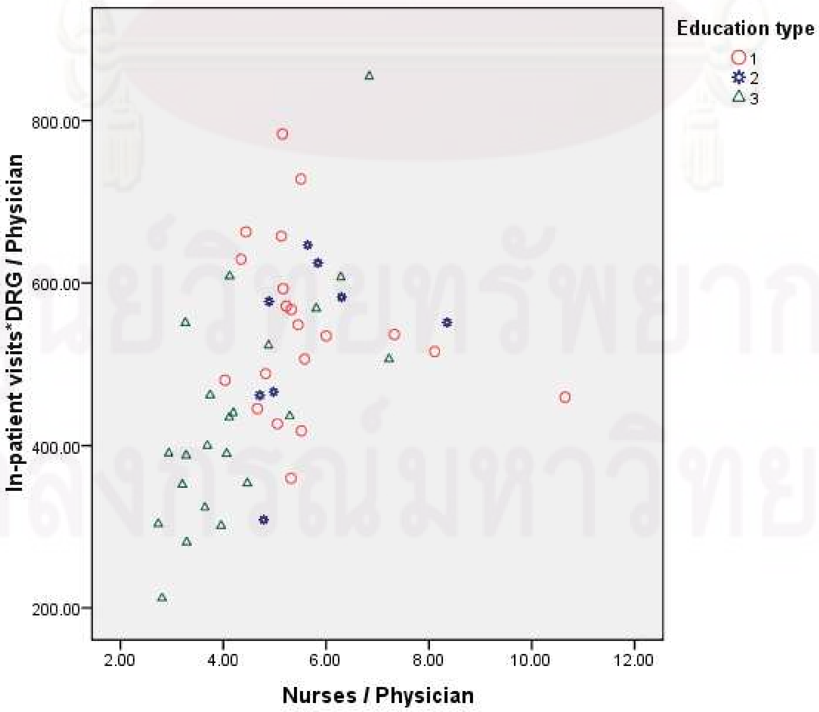


Figure 4-8 Relation between in-patient visits*DRG per physician and nurses per physician



While the relation between in-patient visits adjusted with relative weight of DRG per physician and graduated medical student per physician staff, the relation between in-patient visits adjusted with relative weight of DRG per physician and trained interns per physician staff, and the relation between in-patient visits adjusted with relative weight of DRG per physician and trained residents per physician staff did not definitely correlate together as Figure H3-H5.

Medical education service

- **Medical student teaching**

The relation between graduated medical student per physician staff and beds per physician, the relation between graduated medical student per physician staff and nurses per physician, the relation between graduated medical student per physician staff and trained interns per physician staff, and the relation between graduated medical student per physician staff and trained residents per physician staff did not definitely correlate together as Figure H6-H9.

- **Intern training**

The relation between trained interns per physician staff and beds per physician and the relation between trained interns per physician staff and nurses per physician did not definitely correlate together as Figure H10-H11.

- **Resident training**

The relation between trained residents per physician staff and beds per physician, the relation between trained residents per physician staff and nurses per physician, and the relation between trained residents per physician staff and trained interns per physician staff did not definitely correlate together too as Figure H12-H14.

4.5 Discussion

This part discusses in four parts as following:

1) The whole picture of the results
2) Comparison between the results of both input- and output-orientated DEA
3) Comparison between the results of regression analyses from both input- and output-orientated DEA
4) Comparison between the expected signs and the signs from regression analyses

4.5.1 The whole picture of the results

1) Number of input and output items of DEA

In this study showed that twenty five DMUs in year 2008 can be calculate by DEA (as Table B1) and regression analysis (as Table E1-E4) but the results of regression analysis can not interpret because all coefficients of explanatory variables were insignificant. If the number of DMUs (n) is less than the combined number of inputs and outputs (m + s), a large portion of the DMUs will be identified as efficient and efficiency discrimination among DMUs is lost. Therefore, it is desirable that n exceed m + s by several times (Cooper, Seiford, & Tone, 2002: 103). As in statistics or other empirically oriented methodologies, there is a problem involving degrees of freedom, which is compounded in DEA because of its orientation to *relative* efficiency. In the envelopment model, the number of degrees of freedom will increase with the number of DMUs and decrease with the number of inputs and outputs. A rough rule of thumb which can recommend guidance is as follows.

$$n \geq \max \{m \times s, 3(m + s)\}$$

where n = number of DMUs, m = number of inputs and s = number of outputs (Cooper, Seiford, & Tone, 2002: 252). In this study, there were four multiple inputs, five multiple outputs and twenty-five numbers of DMUs in year 2008 so n = 25, m = 4, s = 5, but 25 < 3(4 + 5) or $n < \max \{m \times s, 3(m + s)\}$. The result was different from the recommendation of Cooper and et al, 2002 that the number of DMUs was a little bit less than the maximum number of the number of inputs plus number of outputs of DEA.

For the study in year 2008, the results of regression analysis showed all coefficients of explanatory variables were insignificant because there were twelve explanatory variables which were too many relative to a small number of observations or DMUs. Hence, this study used the panel data of two years; 2007-2008, which increased double from 25 to 50 DMUs, and the results of regression analyses were better.

2) Skew distribution of efficiency scores

In the past studies, the average efficiency scores used mean for presentation and comparison; for example, when comparing U.S studies with studies from other European countries Hollingsworth et al. (1999) found a greater potential for improvement in the U. S. with an average efficiency score of 0.85, and a range of 0.60 – 0.98, in contrast to Europe with an average efficiency score of 0.91, and a range of 0.88-0.93. The distribution of DEA scores is so skewed, (given the huge spike of efficient units), that reliance on the usual measures of central tendency will be misleading. By excluding the efficient units, the average inefficiency score may be a more reasonable comparison (Cooper, Seiford, & Zhu, 2004: 484-485). In cases of screwed distribution, a mean is not a good average value so the thesis used median for the measure of central tendency of efficiency scores.

4.5.2 Comparison between the results of both input- and output-orientated DEA

The results of both input- & output-orientated DEA were compared in 3 forms classified as compare efficiency scores of both input- & output-orientated DEA, compare efficiency scores by education types of regional hospitals, and compare efficiency scores and education type by ranking.

1) **Comparison of the efficiency scores of both input- and output-orientated DEA**

The results of both input- and output-orientated DEA revealed the different results. Only TECRS scores from both measurements of DEA were the same results but TEVRS and SE scores were the different results. So the interpretation of results of both input- and output-orientated DEA and their regression analyses must be different and researcher should choose a correct one.

TECRS or overall technical efficiency scores (CCR model)

For TECRS scores, there were 31 efficient DMUs from total 50 DMUs and a median score was 1.000 while a minimum was 0.810. Most of inefficient DMUs were in range 85.0-94.9% (84.21% of total inefficient DMUs).

TEVRS or pure technical efficiency scores (BCC model)

For TEVRS scores, there were 36 efficient DMUs from total 50 DMUs and a median score was 1.000; both measurements of DEA, but a minimum of input-orientated DEA was 0.811 while a minimum of output-orientated DEA was 0.817. Most of inefficient DMUs of input-orientated DEA were in range 90.0-99.9% (85.71% of total inefficient DMUs) while most of inefficient DMUs of output-orientated DEA were in range 85.0-99.9% (92.86% of total inefficient DMUs).

If a DMU is fully efficient (100%) in both the CCR and BCC scores, it is operating in the *most productive scale size*. If a DMU has the full BCC efficiency but a low CCR score, then it is operating locally efficient but not globally efficient due to the scale size of the DMU. Thus, it is reasonable to characterize the *scale efficiency* of a DMU by the ratio of the two scores (Cooper, Seiford, & Tone, 2002: 136). So in this study, there were thirty-one DMUs which were the most productive scale size DMUs because they were fully efficient in both the CCR and BCC scores. In addition, there were five DMUs which were operating locally efficiently but not globally efficiently due to the scale size of the DMUs because they had the full BCC efficiency but a low CCR score.

Scale efficiency (SE) scores and the pattern of scale inefficiencies

For SE scores, there were 32 efficient DMUs from total 50 DMUs for input-orientated DEA while there were 31 efficient DMUs from total 50 DMUs for output-orientated DEA and both median scores were 1.000. A minimum of input-orientated DEA was 0.860 while a minimum of output-orientated DEA was 0.889. Most of inefficient DMUs of input-orientated DEA were in range 90.0-99.9% (77.78% of total inefficient DMUs) while most of inefficient DMUs of output-orientated DEA were in range 90.0-99.9% (94.74% of total inefficient DMUs). In addition, most of inefficient DMUs of both measurements of DEA were the increasing returns to scale (irs) pattern of scale inefficiency but they were different in details (irs:drs = 15:3 for input-orientated DEA and irs:drs = 14:5 for output-orientated DEA).

Given the assumption of constant returns to scale, the size of the organization is not considered to be relevant in assessing its relative efficiency. Small organizations can produce outputs with the same ratios of input to output as larger organizations because there are no economies (or diseconomies) of scale present, so doubling all inputs will generally lead to a doubling in all outputs. However, this assumption is inappropriate for services which have economies of scale (or increasing returns to scale). For increasing returns to scale, doubling all inputs should lead to more than a doubling of output because providers are able to spread their overheads more effectively or take advantage of procuring supplies and other items in bulk. For decreasing returns to scale, organizations might become too large and diseconomies of scale (or decreasing returns to scale) could set in. In this case, a doubling of all inputs will lead to less than a doubling of outputs. It would be to an organization's advantage to ensure that its operations are of optimal size-neither too small if there are increasing returns nor too large if there are decreasing returns to scale. If it is likely that the size of service providers will influence their ability to produce services efficiently, the assumption of constant returns to scale is inappropriate. The less restrictive variable returns to scale frontier allows the best practice level of outputs to inputs to vary with the size of the organizations (Bhat, Verma, & Reuben, 2001: 317).

Comparing input- and output-oriented measures of technical efficiency to determine local returns to scale in DEA models

One can infer the nature of local returns to scale at the input- or output-oriented efficient projection of a technically inefficient input-output bundle, when the input- and output-oriented measures of efficiency differ.

Basic Concepts and Definitions:

The production technology faced by firms in an industry producing output vectors (y) from input vectors (x) can be described by the *production possibility set*

$$T = \{(x, y): x \in R_n^{+}; y \in R_m^{+}; y \text{ can be produced from } x\}. \quad (1)$$

An input-output bundle (x, y) is considered feasible if and only if $(x, y) \in T$. The *frontier* of the production possibility set (also known as the *graph of the technology*) is

$$G = \{(x, y): (x, y) \in T; \alpha > 1 \Rightarrow (x, \alpha y) \notin T; \beta < 1 \Rightarrow (\beta x, y) \in T\}. \quad (2)$$

The input-oriented technical efficiency of a feasible input-output bundle (x, y) is

$$\tau_x = \theta^* = \min\theta: (\theta x, y) \in G. \quad (3)$$

Similarly, the output-oriented technical efficiency of the same bundle is
$\tau_y = 1/\phi^*$, where

$$\varphi^* = \max\varphi: (x, \varphi y) \in G. \quad (4)$$

Obviously, $\theta^* \leq 1$ and $\varphi^* \geq 1$.

Theorem 1: If the input-oriented technical efficiency is greater than the output-oriented technical efficiency, then locally increasing returns to scale holds at the efficient input-oriented projection of (x^0, y^0).

Theorem 2: If the output-oriented technical efficiency is greater than the input-oriented technical efficiency, then locally diminishing returns to scale holds at the efficient output-oriented projection of (x^0, y^0).

An implication of the above is that when input-oriented technical efficiency is higher than the output-oriented, the firm would need to increase its output scale in order to attain the most productive scale size, once input-inefficiency is eliminated. Similarly, if output-efficiency is higher, the firm needs to scale down after eliminating output inefficiency. One limitation of the methodology proposed here, however, is *that it can be applied only when* $\tau_x \neq \tau_y$ (Ray, 2008).

In conclusion, the technical efficiency scores of regional hospitals in Thailand in year 2007-2008 were very good because most of DMUs performed in efficient level in all three types of efficiency scores of both measurements of DEA in the same scores; overall technical efficiency 62%, pure technical efficiency 72% and scale efficiency 64%. The median score of all three types of efficiency scores of both measurements of DEA were 1.000. The minimum scores of overall technical efficiency of both measurements of DEA were 0.810 but the minimum scores of pure technical efficiency and scale efficiency scores were different. For input-orientated DEA; the minimum scores were 0.811 for pure technical efficiency and 0.860 for scale efficiency. For output-orientated DEA; the minimum scores were 0.817 for pure technical efficiency and 0.889 for scale efficiency. However, the minimum scores of all three types of efficiency scores of both measurements of DEA in this study were rather high. In addition, most of inefficient DMUs of both measurements of DEA were the increasing return to scale (irs) pattern of scale inefficiency but they were different in details (irs:drs = 15:3 for input-orientated DEA and irs:drs = 14:5 for output-orientated DEA). So the increasing return to scale pattern hospitals are improved through up-sizing and the decreasing return to scale pattern hospitals are improved through down-sizing.

2) Comparison of the efficiency scores by education types of regional hospitals

Regional hospitals in Thailand in year 2007-2008 can be classified to 2 groups by medical educational service; teaching and non-teaching hospitals, there were 20 non-teaching hospitals (DMUs) and 30 teaching hospitals (DMUs). Teaching hospitals can be divided into 2 subgroups as undergraduate teaching hospitals (8 DMUs) and combined undergraduate and postgraduate teaching hospitals (22 DMUs). So the educational types of regional hospitals in this study were classified to 3 types: type 1 = non-teaching hospitals, type 2 = only undergraduate teaching hospitals and type 3 = combined undergraduate and postgraduate teaching hospitals. Many recently studies have been innovative hospital-level studies potentially useful for policy makers and allow policy makers to make fair comparisons of teaching and non-teaching hospitals (Cooper, Seiford, & Zhu, 2004: 486).

TECRS or overall technical efficiency scores (CCR model)

The results of TECRS scores of both measurements of DEA found that were the same results. In group of non-teaching hospitals, there were inefficient hospitals (55%) more than efficient hospitals (45%). But in group of teaching hospitals; both educational type 2 and type 3 hospitals, there were efficient hospitals (62.5%, 77.27%) more than inefficient hospitals (37.5%, 22.73% respectively). So teaching hospitals (73.33%) were more efficient than non-teaching hospitals (45%).

In cases of inefficient hospitals which had TECRS scores less than 1. The results of both measurements of DEA found that were the same results. In group of non-teaching regional hospitals, most of them were in range 85.0-94.9%. In addition, all teaching hospitals were in range 85.0-94.9%.

TEVRS or pure technical efficiency scores (BCC model)

The results of TEVRS scores of both measurements of DEA found that were the same results. Both non-teaching and teaching hospitals, there were efficient hospitals (65%, 76.67%) more than inefficient hospitals (35%, 23.33% respectively) and teaching hospitals (76.67%) were more efficient than non-teaching hospitals (65%). In group of teaching hospitals, educational type 3 hospitals (81.82%) were more efficient than educational type 2 hospitals (62.5%).

In cases of inefficient hospitals which had TEVRS scores less than 1. The results of both measurements of DEA found that were the different results. Total frequencies of each educational type of inefficient hospitals from both measurements of DEA were same**,** but the detail of each level of inefficient hospitals was different.

Scale efficiency (SE) scores and the pattern of scale inefficiencies

Scale efficiency analyzed about SE scores of both measurements of DEA and focused on educational types of regional hospitals. The results of both measurements of DEA found that some results were same and some results were different. For the same results of both measurements of DEA, in group of non-teaching hospitals, there were inefficient hospitals (55%) more than efficient hospitals (45%). But in group of teaching hospitals; both educational type 2 and type 3 hospitals, there were efficient hospitals (75% and 77.27% for input-orientated, 62.5% and 77.27% for output-orientated) more than inefficient hospitals (25% and 22.73% for input-orientated, 37.5% and 22.73% for output-orientated respectively). So teaching hospitals (76.67% for input-orientated, 73.33% for output-orientated) were more efficient than non-teaching hospitals (45% for both measurements of DEA). For the different results of both measurements of DEA, there were different in detail of frequencies of only educational type 2 hospitals.

There were the increasing returns to scale more than the decreasing returns to scale in educational type 1 (irs:drs = 10:1 for input-orientated, irs:drs = 9:2 for output-orientated) and type 3 (irs:drs = 4:1) of both measurements of DEA, but they were different in details of frequencies of the pattern of scale inefficiencies. In educational type 2 hospitals of input-orientated DEA, the frequency of increasing return to scale was as same as the frequency of decreasing return to scale (irs = drs = 1); however, in educational type 2 hospitals of output-orientated DEA, the frequencies of decreasing return to scale (drs = 2) were more than the frequencies of increasing return to scale (irs = 1).

In cases of inefficient hospitals which had SE scores less than 1. The results of both measurements of DEA found that were near totally different results. The frequencies of educational type 1 and type 2 from both measurements of DEA were the different results but the frequencies of educational type 3 from both measurements of DEA were the same results.

In conclusion for medical education services, all three types of efficiency scores of both measurements of DEA had the same results but there were different in details. The results revealed teaching hospitals were more efficient than non-teaching hospitals as the previous studies (Grosskopf, Margaritis, & Valdmanis, 2001; Grosskopf, Margaritis, & Valdmanis, 2004) and a subgroup of combined undergraduate and postgraduate teaching regional hospitals was the most efficient group. If offering many services together is more efficient, then economies of scope exist (Cooper, Seiford, & Zhu, 2004: 513). These results supported large hospitals, medium sized hospitals, and closing or restructuring smaller hospitals like the previous study (McCallion, McKillop, Glass, & Kerr, 1999: 27-32).

3) Comparison of the efficiency scores and education type by ranking

The results of efficiency scores and education type of both types of DEA were compared by ranking in order and found that only overall technical efficiency scores were not different in both types of DEA. The results of pure technical efficiency scores found that all efficient DMUs of both types of DEA were same but most of inefficient DMUs of both types of DEA were different except the last two inefficient DMUs were same (the 15th DMU was in educational type 2 and the 22th DMU was in educational type 1). The results of scale efficiency scores found that most of efficient DMUs of both types of DEA were same except one DMU (the 40th DMU) which changed from efficient DMU of scale efficiency of input-orientated DEA to inefficient DMU of scale efficiency of output-orientated DEA. However, all of inefficient DMUs of both types of scale efficiency scores were totally different in sequence, pattern of scale inefficiency and education type. The advantages of DEA were noted in terms of (a) its ability to identify sources and amounts of inefficiency in each input and each output for each entity (hospital, store, furnace, etc.) and (*b*) its ability to identify the benchmark members of the efficient set used to effect these evaluations and identify these sources (and amounts) of inefficiency. (Cooper, Seiford, & Tone, 2002: 14).

4.5.3 Comparison between the results of regression analyses from both input- and output-orientated DEA

The results of regression analyses from both measurements of DEA revealed the similarities and differences as following.

TEVRS or pure technical efficiency scores (BCC model)

For TEVRS scores, the results of regression analyses from both measurements of DEA were compared in details of Table 4-24 and 4-26. Most explanatory variables of TEVRSi scores significantly correlated to TEVRSi scores except only RPS insignificantly correlated to TEVRSi scores while the explanatory variables of TEVRSo scores significantly correlated to TEVRSo scores less than TEVRSi scores and there were three explanatory variables which insignificantly correlated to TEVRSo scores such as P, P^2 and RPS. The signs of coefficients of explanatory variable of TEVRSi and TEVRSo scores were not different. Both estimated equations had three explanatory variables which reversely correlated to TEVRSi and TEVRSo scores such as BP, P and OPP. The remaining explanatory variables directly correlated to TEVRSi and TEVRSo scores. In addition, these different results affected the interpretation of regression analysis.

R-squared value, probability (F-statistic) and Durbin-Watson stat of both TEVRS scores were a little bit different and R-squared values (R^2) from both estimated equations were slightly low (R^2 = 0.380479 for TEVRSi scores and R^2 = 0.372030 for TEVRSo scores). For the detections of autocorrelation, multicollinearity, and heteroscedasticity problems of both estimated equations, they did not found all problems.

The coefficient values of explanatory variable of TEVRSi and TEVRSo scores were a little bit different as the equations 4-5 and 4-7 below. The signs of coefficients of explanatory variable of TEVRSi and TEVRSo scores were not different as the equations 4-5 and 4-7 and summarized in Table 4-28 below.

$$\text{TEVRSi scores} = 1.193648 - 0.027043BP - 0.001455P + 3.26E\text{-}06P^2 + 0.018173NP - 0.008207OPP + 0.182930IPS + 0.222389RPS \quad (4\text{-}5)$$

$$\text{TEVRSo scores} = 1.136643 - 0.029290BP - 0.001107P + 2.48E\text{-}06P^2 + 0.023639NP - 0.008336OPP + 0.208326IPS + 0.266873RPS \quad (4\text{-}7)$$

Scale efficiency (SE) scores

For SE scores, the results of regression analyses from both measurements of DEA were compared in details of Table 4-25 and 4-27. Most explanatory variables insignificantly correlated to both SEi and SEo scores, only two explanatory variables; IDRGP and U_j, significantly correlated to SEi scores while only one explanatory variable; IDRGP, significantly correlated to SEo scores. The signs of coefficients of explanatory variable of SEi and SEo scores were not different. There was one explanatory variable; OP, which reversely correlated to both SEi and SEo scores. The remaining explanatory variables directly correlated to both SEi and SEo scores. In addition, these different results affected the interpretation of regression analysis.

R-squared value, probability (F-statistic) and Durbin-Watson stat of both SE scores were a little bit different and R-squared values (R^2) from both estimated equations were slightly low (R^2 = 0.230247 for SEi scores and R^2 = 0.231005 for SEo scores); in addition, R^2 from both SEi and SEo scores were less than R^2 from both TEVRSi and TEVRSo scores. For the detections of autocorrelation, multicollinearity, and heteroscedasticity problems of both estimated equations, they did not found all problems.

The coefficient values of explanatory variable of SEi and SEo scores were a little bit different as the equations 4-6 and 4-8 below. But the signs of coefficients of explanatory variable of SEi and SEo scores were not different as the equations 4-6 and 4-8 and summarized in Table 4-29 below.

$$\text{SEi scores} = 0.897460 - 4.34\text{E-}06\text{OP} + 0.000152\text{IDRGP} + 0.044599\text{MPS} + 0.036886\text{U}_j + 0.016369\text{HA}_j \quad (4\text{-}6)$$

$$\text{SEo scores} = 0.928444 - 4.39\text{E-}06\text{OP} + 0.000110\text{IDRGP} + 0.033221\text{MPS} + 0.025174\text{U}_j + 0.014607\text{HA}_j \quad (4\text{-}8)$$

4.5.4 The results of regression analyses from input- or output-orientated DEA

The results of regression analyses both measurements of DEA were different so the interpretation of the results was different too.

Results of regression analyses from input-orientated DEA

There were six explanatory variables of pure technical efficiency scores significantly correlated to pure technical efficiency scores of input-orientated DEA. The results of regression analysis revealed the numbers of physicians in form of square (P^2), nurses-physician ratio (NP) and trained interns-physician staff ratio (IPS) positively correlated to pure technical efficiency scores; however, beds-physician ratio (BP), numbers of physicians (P) and other personnel-physician ratio (OPP) negatively correlated to pure technical efficiency scores. And the most influential explanatory variable of pure technical efficiency scores was a trained interns-physician staff ratio (IPS). It can explain that if beds-physician ratio (BP) decreased one unit, TEVRSi scores tended to increase 0.027043 units, giving other things were constant. If number of physicians (P) decreased one unit, TEVRSi scores tended to increase 0.001455 units, giving other things were constant. If number of physicians in form of square (P^2) increased one unit, TEVRSi scores tended to increase 3.26E-06 units (very low, insignificant), giving other things were constant. If nurses-physician ratio (NP) increased one unit, TEVRSi scores tended to increase 0.018173 units, giving other things were constant. If other personnel-physician ratio (OPP) decreased one unit, TEVRSi scores tended to increase 0.008207 units, giving other things were constant. If trained interns-physician staff ratio (IPS) increased one unit, TEVRSi scores tended to increase 0.182930 units, giving other things were constant. And the most influential explanatory variable of TEVRSi scores was a trained interns-physician staff ratio (IPS) because its coefficient had the highest value among significant explanatory variables. For input-orientated DEA, only deficiency of nurse was the main problem so hospital managers should increase the numbers of nurses for increasing pure technical efficiency of regional hospitals. While the numbers of physicians and other personnel should be decrease for increasing pure technical efficiency of regional hospitals.

For scale efficiency scores, the results of regression analysis revealed only IDRGP and Ui significantly correlated to scale efficiency scores. If in-patient visits adjusted with relative weight of DRG per physician (IDRGP) increased one unit, scale efficiency scores tended to increase 0.000152 units, giving other things were constant. If location of regional hospital staying near University hospital (U_1), scale efficiency scores tended to increase 0.036886 units comparing with regional hospital not staying near University hospital (U_0), giving other things were constant. And the most influential explanatory variable of scale efficiency scores was location of regional hospital staying near University hospital (U_j) because its coefficient had the highest value among significant explanatory variables.

In conclusion, policy makers in health sector and hospital managers can improve the inefficient regional hospitals in proper direction by analyzing each inefficient regional hospital and supported the positive determinants by increasing the numbers of nurses and interns to regional hospitals for increasing pure technical efficiency scores. In addition, the increasing of trained interns-physician staff ratio was the most influential determinant. However, the hospital managers should reduce the numbers of physicians, the ratio of beds per physician and the ratio of other personnel per physician for increasing pure technical efficiency scores because these were the negative determinants of hospital efficiency. For scale efficiency, the in-patient visits adjusted with relative weight of DRG per physician and the location of regional hospital staying near University hospital (U_j) were the only two positive determinants so the physicians should treat the patients with high quality of care to reduce the complications and manage the patient-care teams well to circulate bed efficiently. The hospital managers should support the technological resources for physicians to efficiently investigate for precise and quick diagnosis and support the patient-care teams to efficiently treat the patients in safety. These should increase the quantities of in-patient visits and increasing the competency to treat the complicated and severe cases will increase the value of average relative weight of DRG. So these will eventually increase the scale efficiency. In addition, the most influential explanatory variable of scale efficiency scores was the location of regional hospital staying near University hospital (U_j) because regional hospital collaborated with University hospital to support together not only health care services but also medical education services. However, this factor can not be controlled by policy makers of Ministry of Public Health and hospital managers of regional hospitals.

Results of regression analyses from output-orientated DEA

There were four explanatory variables of pure technical efficiency scores significantly correlated to pure technical efficiency scores of output-orientated DEA which were less than input-orientated DEA. The results of regression analysis revealed nurses-physician ratio (NP) and trained interns-physician staff ratio (IPS) positively correlated to pure technical efficiency scores; however, beds-physician ratio (BP) and other personnel-physician ratio (OPP) negatively correlated to pure technical efficiency scores. And the most influential explanatory variable of pure technical efficiency scores was a trained interns-physician staff ratio (IPS). If beds-physician ratio (BP) decreased one unit, pure technical efficiency scores tended to increase 0.029290 units, giving other things were constant. If nurses-physician ratio (NP) increased one unit, pure technical efficiency scores tended to increase 0.023639 units, giving other things were constant. If other personnel-physician ratio (OPP) decreased one unit, pure technical efficiency scores tended to increase 0.008336 units, giving other things were constant. If trained interns-physician staff ratio (IPS) increased one unit, pure technical efficiency scores tended to increase 0.208326 units, giving other things were constant. For output-orientated DEA, only deficiency of nurse was the main problem so hospital managers should increase the numbers of nurses while they should decrease the numbers of other personnel for increasing pure technical efficiency of regional hospitals.

For scale efficiency scores, the results of regression analysis revealed only one explanatory variable; IDRGP, which significantly correlated to scale efficiency scores. If in-patient visits adjusted with relative weight of DRG per physician (IDRGP) increased one unit, scale efficiency scores tended to increase 0.000110 units, giving other things were constant.

In conclusion, policy makers in health sector and hospital managers can improve the inefficient regional hospitals in proper direction by analyzing each inefficient regional hospital and supported the positive determinants by increasing the numbers of nurses and interns to regional hospitals for increasing pure technical efficiency scores. In addition, the increasing of trained interns-physician staff ratio was the most influential determinant for increasing pure technical efficiency scores. However, the hospital managers should decrease the ratio of beds per physician and the ratio of other personnel per physician for increasing pure technical efficiency scores because these were the negative determinants of hospital efficiency. For scale efficiency, in-patient visits adjusted with relative weight of DRG per physician was the only one positive determinant so the physicians should treat the patients with high quality of care to reduce the complications and manage the patient-care teams well to circulate bed efficiently. The hospital managers should support the technological resources for physicians to efficiently investigate for precise and quick diagnosis and support the patient-care teams to efficiently treat the patients in safety. These should increase the quantities of in-patient visits and increasing the competency to treat the complicated and severe cases will increase the value of average relative weight of DRG. So these will eventually increase the scale efficiency.

4.5.5 Comparison between the expected signs and the signs from regression analyses

- **The signs of coefficients of explanatory variables of TEVRS scores**

Most signs of coefficients of explanatory variable of TEVRS scores from the results of regression analyses and the expected signs before run regression analyses were same such as BP_{it}, P_{it}^2, NP_{it}, IPS_{it}, and RPS_{it} as presented in Table 3-6 and 4-28. But only two signs of coefficients of explanatory variable of TEVRS scores from the results of regression analyses and the expected signs before run regression analyses were different such as P_{it} and OPP_{it}. From the results of regression analyses surprisingly revealed that p-value of the numbers of physicians (P) from TEVRSi scores was significant but from TEVRSo scores was insignificant. Physician was expected to be the most important labor factor of both health care services and medical education services of regional hospitals and this was true only pure technical efficiency from input-orientated DEA but this was not true in pure technical efficiency from output-orientated DEA. The results implied the other input labor; nurse, was the most important labor factor of both health care services and medical education services of regional hospitals for output-orientated DEA because only nurses-physician ratio (NP) was significant input labor and had positive sign so the deficiency's problem of nurses was more serious than the deficiency's problem of physicians in regional hospitals in year 2007-2008. While other personnel-physician ratio (OPP) was the other one which the expected signs and the sign from the results of regression analyses were different and show a negative sign that implied the over numbers of other personnel relative to the numbers of physicians in regional hospitals in year 2007-2008.

Table 4-28 The signs of coefficients of explanatory variable of TEVRSi and TEVRSo scores

Dependent variables	Signs of coefficients of explanatory variables of TEVRS scores						
	BP_{it}	P_{it}	P_{it}^2	NP_{it}	OPP_{it}	IPS_{it}	RPS_{it}
TEVRS $scores_{it}$	-	-	+	+	-	+	+

- **The signs of coefficients of explanatory variables of SE scores**

All signs of coefficients of explanatory variable of SE scores from the results of regression analyses and the expected signs before run regression analyses were same as presented in Table 3-8 and 4-29 so the results followed the assumption.

Table 4-29 The signs of coefficients of explanatory variable of SEi and SEo scores

Dependent variables	Signs of coefficients of explanatory variables of SE scores				
	OP_{it}	$IDRGP_{it}$	MPS_{it}	U_{1it}	HA_{1it}
SE $scores_{it}$	-	+	+	+	+

CHAPTER V

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The objectives of this study are to measure hospital efficiency of regional hospitals in Thailand in the year 2007-2008 using DEA technique and identify the determinants of hospital efficiency using regression analysis. This study used output-orientated measurement DEA instead of input-orientated measurement because the situation of regional hospitals in those years faced with the problems of the insufficient resources including personnel, budgets and medical equipments. In addition, the chance of increasing of physician staffs, nurses and budgets in regional hospitals in those years was not easy like input fix so measuring the maximum of output mix fit to output-orientated DEA. The results are analyzed in three aspects.

1. Analysis of hospital efficiency (output-orientated DEA)
2. Analysis of determinants of hospital efficiency
3. Analysis of relation between determinants

5.1.1 Analysis of hospital efficiency (output-orientated DEA)

The results of output-orientated DEA revealed, there were 31 efficient DMUs from total 50 DMUs from overall technical efficiency scores and a median score was 1.000 while a minimum was 0.810. Most of inefficient DMUs were in range 85.0-94.9% (84.21% of total inefficient DMUs). There were 36 efficient DMUs from total 50 DMUs from pure technical efficiency scores and a median score was 1.000 while a minimum was 0.817. Most of inefficient DMUs were in range 85.0-99.9% (92.86% of total inefficient DMUs). For scale efficiency scores, there were 31 efficient DMUs from total 50 DMUs and a median score was 1.000 while a minimum was 0.889. Most of inefficient DMUs were in range 90.0-99.9% (94.74% of total inefficient DMUs). In addition, most of patterns of scale inefficiency were the increasing returns to scale (irs:drs = 14:5).

In medical education services, the educational types of regional hospitals in this study were classified to 3 types: type 1 = non-teaching hospitals, type 2 = only undergraduate teaching hospitals and type 3 = combined undergraduate and postgraduate teaching hospitals. For overall technical efficiency, pure technical efficiency and scale efficiency scores, teaching hospitals (73.33%, 76.67%, and 73.33%) were more efficient than non-teaching hospitals (45%, 65%, and 45% respectively) and the educational type 3 was the most efficient. There were the increasing returns to scale of inefficient hospitals more than decreasing returns to scale of inefficient hospitals in both educational type 1 (irs:drs = 9:2) and type 3 (irs:drs = 4:1) hospitals. But in educational type 2 hospitals, the frequencies of decreasing return to scale (drs = 2) were more than the frequencies of increasing return to scale (irs = 1).

In conclusion, the technical efficiency scores of regional hospitals in Thailand in year 2007-2008 were very good because most of DMUs performed in efficient level in all three types of efficiency scores; overall technical efficiency 62%, pure technical efficiency 72% and scale efficiency 64%. The median score of all three types of efficiency scores were 1.000. The minimum scores of all three types of efficiency scores were rather high; 0.810 for overall technical efficiency, 0.817 for pure technical efficiency and 0.889 for scale efficiency. In medical education services, teaching hospitals (73.33%, 76.67%, and 73.33%) were more efficient than non-teaching hospitals (45%, 65%, and 45% for overall technical efficiency, pure technical efficiency and scale efficiency, respectively) and a subgroup of combined undergraduate and postgraduate teaching regional hospitals was the most efficient group.

All above information could be useful for policy makers in health sector and hospital managers to improve the inefficient regional hospitals in proper direction by analyzing each inefficient regional hospital and supported medical education services in potential regional hospitals because teaching hospitals were more efficient than non-teaching hospitals. In addition, policy makers should encourage some regional hospitals which have competency to perform combining undergraduate and postgraduate teaching in hospitals because this group of hospitals was the most efficient group.

5.1.2 Analysis of determinants of hospital efficiency

The results of regression analysis revealed nurses-physician ratio (NP) and trained interns-physician staff ratio (IPS) positively correlated to pure technical efficiency scores; however, beds-physician ratio (BP) and other personnel-physician ratio (OPP) negatively correlated to pure technical efficiency scores. And the most influential explanatory variable of pure technical efficiency scores was a trained interns-physician staff ratio (IPS). If beds-physician ratio (BP) decreased one unit, pure technical efficiency scores tended to increase 0.029290 units, giving other things were constant. If nurses-physician ratio (NP) increased one unit, pure technical efficiency scores tended to increase 0.023639 units, giving other things were constant. If other personnel-physician ratio (OPP) decreased one unit, pure technical efficiency scores tended to increase 0.008336 units, giving other things were constant. If trained interns-physician staff ratio (IPS) increased one unit, pure technical efficiency scores tended to increase 0.208326 units, giving other things were constant.

For scale efficiency scores, the results of regression analysis revealed only one explanatory variable; IDRGP, which significantly correlated to scale efficiency scores. If in-patient visits adjusted with relative weight of DRG per physician (IDRGP) increased one unit, scale efficiency scores tended to increase 0.000110 units, giving other things were constant.

In conclusion, policy makers in health sector and hospital managers can improve the inefficient regional hospitals in proper direction by analyzing each inefficient regional hospital and supported the positive determinants by increasing the numbers of nurses and interns to regional hospitals for increasing pure technical efficiency scores. In addition, the increasing of trained interns-physician staff ratio was the most influential determinant. However, the hospital managers should reduce the ratio of beds per physician and the ratio of other personnel per physician for increasing pure technical efficiency scores because these were the negative determinants of hospital efficiency. For scale efficiency, the in-patient visits adjusted with relative weight of DRG per physician was the only one positive determinant so the physicians should treat the patients with high quality of care to reduce the complications and manage the patient-care teams well to circulate bed efficiently. The hospital managers should support the technological resources for physicians to efficiently investigate for precise and quick diagnosis and support the patient-care teams to efficiently treat the patients in safety.

5.1.3 Analysis of relation between determinants

Relation between resources

Both the relation between beds-physician ratio (BP) and nurses-physician ratio (NP), and the relation between other personnel-physician ratio (OPP) and nurses-physician ratio (NP) revealed a linear relationship with positive slope that meant the more beds required the more human resources (proportionally increased physicians, nurses and other personnel). In subgroup of combined undergraduate and postgraduate teaching regional hospitals, the physicians consumed human resources (both nurses and other personnel) less than both a subgroup of undergraduate teaching regional hospitals and a group of non-teaching hospitals because the complicate works of physicians and physician staffs in a subgroup of combined undergraduate and postgraduate teaching regional hospitals can not be substituted by other medical personnel.

Health care services

The relation between the out-patient visits per physician and the in-patient visits per physician related to consume resources (beds, nurses) and to produce the trained interns that distributed like three groups classified by educational type. Teaching regional hospitals (both educational type 2 and type 3) can produce the out-patient visits per physician and the in-patient visits adjusted with relative weight of DRG per physician less than non-teaching regional hospitals; in addition, teaching regional hospitals consumed resources (beds and nurses) and produced the trained interns less than non-teaching regional hospitals. Among teaching hospitals, a subgroup of combined undergraduate and postgraduate teaching regional hospitals can produce out-patient visits per physician and in-patient visits adjusted with relative weight of DRG per physician (health care services) less than a subgroup of undergraduate teaching regional hospitals; in addition, a subgroup of combined undergraduate and postgraduate teaching regional hospitals consumed resources (beds, nurses) and produced the trained interns less than a subgroup of undergraduate teaching regional hospitals, because the complicate works of physicians and physician staffs in a subgroup of combined undergraduate and postgraduate teaching regional hospitals can not be substituted by other medical personnel.

Medical education care service

There were no relation between medical education services both undergraduate (medical student teaching) and postgraduate levels (residency training) and input resources (beds and nurses).

5.2 Limitation of the study

DEA in health care study, there are many types of inputs and outputs to calculation for evaluation of the technical efficiency or hospital efficiency. For hospital efficiency, types of inputs are numbers of beds, physicians, nurses, other personnel, and costs (operating expenses and capital investment, labor costs, and supply and non-labor costs). Types of outputs are the numbers of total out-patient visits, in-patient visits, inpatient days, in-patient visits adjusted with relative weight of DRG (in-patient visits*DRG), graduated medical student, trained interns, trained residents. Selection of inputs and outputs for DEA depends on the objective and limitation of the study. There are many limitations in this study as following:

1. A small numbers of the observations. There are only 25 observations including all regional hospitals in Thailand.
2. Data availability. Although the usage of panel data can apply to increase in the numbers of observations and compare the efficiencies in the different years, data availability is only after year 2007. Data before year 2007, some data sources can not support. Personnel Administration Division, Office of the Permanent Secretary, Ministry of Public Health can not support the exact numbers of each type of hospital personnel because of the movement problem of civil servants and this division supports only some personnel such as civil servants and permanent servants. Thailand government limited the civil servant system and tried to decrease the numbers of these personnel so there were a large numbers of temporary servants in all regional hospitals except groups of physicians, dentists and pharmacists. So the data of exact numbers of some personnel was directly collected from the regional hospitals which it spent a lot of time.
3. Time limitation. There was only one month for data collection and time schedule of this thesis must send the first draft of thesis for advisor to approve on April, 1st but some data in year 2009 will be available after the end of March.

So this thesis limits only four important multiple inputs and five multiple outputs for DEA and twelve essential explanatory variables for regression analysis.

5.3 Recommendations

From the results of this study, some policy implications and recommendations can be derived:

1. Teaching regional hospitals were more efficient than non-teaching regional hospitals and the combined undergraduate and postgraduate teaching hospital was the most efficient group of regional hospitals. Hence, the policy makers in health sector and hospital managers should support medical education services in potential regional hospitals and encourage some regional hospitals which have competency to perform combining undergraduate and postgraduate teaching in hospitals.

2. The policy makers in health sector and hospital managers should support the positive determinants by increasing the numbers of nurses and interns to increase pure technical efficiency of regional hospitals.
3. In cases of inefficient regional hospitals, the pattern of scale inefficiency should be analyzed for the policy makers in health sector and hospital managers that have the guideline to improve scale efficiency of the inefficient hospitals in the proper direction such as the increasing return to scale pattern hospitals are improved through up-sizing and the decreasing return to scale pattern hospitals are improved through down-sizing. In addition, the details of each inefficient hospital should be explored and analyzed with the information from DEA and regression analyses.
4. Efficiency monitoring and benchmarking. If the Ministry of Public Health sets the national policy in health care services or/and medication services for standardization in each level of public hospital, the hospital efficiency monitoring and benchmarking should be routinely measured and reported yearly, or every two or three years. This is sensitive issue for inefficient hospitals so the reports should not identify the inefficient hospitals but the results should be reported in other words or in the classified groups such as good, moderate, fair, poor depending on the levels of efficiency scores. These criteria are set for benchmarking, standardization and continuous improvement of organization, not for blame.
5. Selection of observers for evaluation of hospital efficiency. If hospital efficiency is used to efficiency monitoring and benchmarking like national policy, the selection of observers for evaluation of hospital efficiency should be careful because it is relatively compare together in chosen multiple inputs and outputs. So the comparable hospitals should have the same context for fairness of evaluation, they are not much different in hospital competency which can classify by levels of hospitals such as community hospital level, general hospital level, regional hospital level, and university hospital level.
6. Validity and reliability of data. The results of DEA and regression analysis are used to evaluate the efficiency of organizations so they directly impact to observers both positive and negative results so the correct data for calculation are very important. If the wrong data is used for calculation, the wrong results will be used to interpret and bring to the serious problems in the future so the assessors should be careful about validity and reliability of data so much.

5.4 Recommendation for further study

In the future, allocative efficiency and qualitative study combining with quantitative study should be very helpful for policy maker in health sector and hospital managers to improve inefficient hospitals to efficient hospitals in the proper direction of each hospital.

1. Allocative efficiency (AE). Given measures of cost efficiency (CE) and technical efficiency (TE), allocative efficiency can be calculated as AE = CE/TE. By comparing the technically efficient levels of inputs, one can determine which inputs are over- utilized or under-utilized relative to their cost minimizing levels. This information will help the policy makers in health sector to properly allocate the budget under constraint. If allocative efficiency is used to evaluate efficiency, only input-orientated measurement DEA can be applied for cost minimization.

2. Qualitative study. Qualitative study integrates with quantitative study to get more detail of information about limitations of each regional hospital, causes of hospital inefficiency, common and individual determinants of hospital efficiency or inefficiency in each regional hospital. Information from both qualitative and quantitative studies is valuable for hospital director and management committee to improve their inefficient hospital in proper direction combining with using the efficient hospitals as a good model or best practice. Qualitative study about hospital management is not easy and issue about hospital efficiency is very sensitive, subjective, time and budget consuming study so these studies require the good teamwork of assessors.

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APPENDICES

Appendix A Data of DEA

Table A1 Input mix data of DEA

Hospital No. (DMU)		Beds		Total physicians		Nurses		Other personnel	
2007	2008	2007	2008	2007	2008	2007	2008	2007	2008
1	26	445	445	90	93	434	486	868	844
2	27	680	680	139	151	565	566	943	1003
3	28	825	825	262	261	735	714	1461	1466
4	29	555	555	85	98	452	457	356	381
5	30	733	733	171	166	623	613	1135	1180
6	31	505	505	54	61	438	447	645	721
7	32	1019	1019	262	275	1078	1134	1759	1774
8	33	590	590	90	91	400	469	781	725
9	34	697	697	103	100	532	551	964	1016
10	35	1000	1000	178	185	1126	1272	1686	1718
11	36	867	867	245	232	720	757	1461	1566
12	37	806	806	144	152	785	780	1135	1227
13	38	800	800	151	154	752	753	1277	1330
14	39	561	561	111	114	531	537	1020	1014
15	40	756	756	111	126	700	711	1241	1351
16	41	653	653	147	155	657	650	959	1002
17	42	905	905	204	222	807	728	1256	1288
18	43	855	855	123	132	651	644	1110	1171
19	44	602	602	89	87	450	463	643	668
20	45	552	552	124	118	500	513	1017	946
21	46	931	931	107	133	773	773	1075	1063
22	47	760	760	111	120	666	701	1215	664
23	48	596	596	187	203	615	651	1287	1309
24	49	474	474	79	79	436	441	902	946
25	50	452	452	54	64	575	535	795	947

Table A2 Output mix data of DEA

Hospital No. (DMU)		Out-patient visits		In-patient visits*DRG		Graduate medical student		Trained interns		Trained residents	
2007	2008	2007	2008	2007	2008	2007	2008	2007	2008	2007	2008
1	26	500665	538176	43960.05	53160	0	0	15	9	0	0
2	27	666804	687480	54232.66	69754.3	31	31	22	15	0	2
3	28	665228	697710	55586.56	79229.92	21	7	19	18	18	21
4	29	398482	407184	30567.05	43661.85	0	0	12	14	0	0
5	30	414407	456656	55393.35	66401.58	10	9	23	20	14	14
6	31	283726	299409	27844.08	32722.03	0	0	7	10	0	0
7	32	633859	613863	113912.1	167362.44	25	32	40	30	8	11
8	33	359577	461974	59681.88	71302.14	0	0	24	15	0	0

9	34	471156	433926	61053.49	72811.44	0	0	24	14	0	0
10	35	503278	571633	108723.2	158882.1	0	4	46	32	0	1
11	36	702874	743009	95715	127929.6	30	26	38	30	6	14
12	37	701165	721090	79005.72	99970.4	0	0	35	27	0	0
13	38	740255	702899	70381.11	88903.44	29	27	21	25	0	0
14	39	320557	468110	34226.5	52635.7	25	28	16	17	0	0
15	40	514064	539527	64648.26	81463.73	0	0	15	22	0	0
16	41	520580	552776	51970.2	68238.8	16	22	23	19	1	1
17	42	702907	765112	61469.28	86095.42	62	56	29	31	2	1
18	43	481517	576783	53647.34	69054.96	15	17	10	10	4	5
19	44	363937	394649	37975.6	49363.14	0	0	16	12	0	0
20	45	600419	716395	59545.2	74249.68	0	0	20	12	0	0
21	46	452287	447854	54209.12	75624.56	14	15	10	29	0	1
22	47	508535	532701	59359	74965.76	0	0	13	18	0	0
23	48	537479	513666	52589.06	71464.32	21	20	15	22	9	8
24	49	400214	429426	33019.11	40023.2	0	0	9	10	0	0
25	50	299672	412400	24811.36	35303.52	0	0	8	7	0	0

Table A3 Frequency of graduated medical student in each DMU

The numbers of graduated medical student in each DMU	Frequency	%
0	25	50.0
4	1	2.0
7	1	2.0
9	1	2.0
10	1	2.0
14	1	2.0
15	2	4.0
16	1	2.0
17	1	2.0
20	1	2.0
21	2	4.0
22	1	2.0
25	2	4.0
26	1	2.0
27	1	2.0
28	1	2.0
29	1	2.0
30	1	2.0
31	2	4.0
32	1	2.0
56	1	2.0
62	1	2.0
Total	50	100.0

Table A4 Frequency of trained residents in each DMU

The numbers of trained residents in each DMU	Frequency	%
0	31	62.0
1	5	10.0
2	2	4.0
4	1	2.0
5	1	2.0
6	1	2.0
8	2	4.0
9	1	2.0
11	1	2.0
14	3	6.0
18	1	2.0
21	1	2.0
Total	50	100.0

Appendix B Results of input- and output-orientated DEA

Table B1 Results of both input- and output-orientated DEA; only year 2008

Hospitals No. (DMU)	TECRS		TEVRS		SE		Pattern of scale inefficiency	
	CRSi	CRSo	VRSi	VRSo	Sei	Seo	RTSi	RTSo
1	0.951	0.951	1	1	0.951	0.951	irs	irs
2	1	1	1	1	1	1	-	-
3	1	1	1	1	1	1	-	-
4	1	1	1	1	1	1	-	-
5	1	1	1	1	1	1	-	-
6	0.98	0.98	1	1	0.98	0.98	irs	irs
7	1	1	1	1	1	1	-	-
8	1	1	1	1	1	1	-	-
9	0.915	0.915	0.926	0.916	0.988	0.999	irs	drs
10	1	1	1	1	1	1	-	-
11	1	1	1	1	1	1	-	-
12	1	1	1	1	1	1	-	-
13	1	1	1	1	1	1	-	-
14	1	1	1	1	1	1	-	-
15	0.954	0.954	0.965	0.955	0.989	1	irs	-
16	0.914	0.914	0.982	0.974	0.93	0.938	irs	irs
17	1	1	1	1	1	1	-	-
18	1	1	1	1	1	1	-	-
19	0.885	0.885	0.984	0.922	0.899	0.96	irs	irs
20	1	1	1	1	1	1	-	-
21	1	1	1	1	1	1	-	-
22	1	1	1	1	1	1	-	-
23	1	1	1	1	1	1	-	-
24	0.955	0.955	1	1	0.955	0.955	irs	irs
25	1	1	1	1	1	1	-	-

Table B2 Frequency of CRSi scores of input-orientated DEA in year 2007-2008

CRSi scores	Frequency	%
0.81	1	2.0
0.85	1	2.0
0.851	1	2.0
0.855	1	2.0
0.858	1	2.0
0.877	1	2.0
0.887	1	2.0
0.889	1	2.0
0.896	1	2.0

0.901	1	2.0
0.905	1	2.0
0.908	1	2.0
0.912	1	2.0
0.915	1	2.0
0.922	1	2.0
0.943	1	2.0
0.945	1	2.0
0.951	1	2.0
0.977	1	2.0
1	31	62.0
Total	50	100.0

Table B3 Frequency of VRSi scores of input-orientated DEA

VRSi scores	Frequency	%
0.811	1	2.0
0.854	1	2.0
0.903	1	2.0
0.908	1	2.0
0.926	1	2.0
0.942	1	2.0
0.947	1	2.0
0.954	1	2.0
0.966	1	2.0
0.982	1	2.0
0.985	1	2.0
0.989	1	2.0
0.993	1	2.0
0.994	1	2.0
1	36	72.0
Total	50	100.0

Table B3Frequency of SEi scores of input-orientated DEA

SEi scores	Frequency	%
0.86	1	2.0
0.889	1	2.0
0.896	1	2.0
0.899	1	2.0
0.901	1	2.0

0.903	1	2.0
0.927	1	2.0
0.929	2	4.0
0.943	1	2.0
0.945	1	2.0
0.951	1	2.0
0.955	1	2.0
0.971	1	2.0
0.988	1	2.0
0.992	1	2.0
0.996	1	2.0
0.999	1	2.0
1	32	64.0
Total	50	100.0

Table B5 Frequency of CRSo scores of output-orientated DEA

CRSo scores	Frequency	%
0.81	1	2.0
0.85	1	2.0
0.851	1	2.0
0.855	1	2.0
0.858	1	2.0
0.877	1	2.0
0.887	1	2.0
0.889	1	2.0
0.896	1	2.0
0.901	1	2.0
0.905	1	2.0
0.908	1	2.0
0.912	1	2.0
0.915	1	2.0
0.922	1	2.0
0.943	1	2.0
0.945	1	2.0
0.951	1	2.0
0.977	1	2.0
1	31	62.0
Total	50	100.0

Table B6 Frequency of VRSo scores of output-orientated DEA

VRSo scores	Frequency	%
0.817	1	2.0
0.862	1	2.0
0.886	1	2.0
0.892	1	2.0
0.894	1	2.0
0.916	1	2.0
0.92	1	2.0
0.923	1	2.0
0.925	1	2.0
0.946	1	2.0
0.954	1	2.0
0.974	1	2.0
0.984	1	2.0
0.985	1	2.0
1	36	72.0
Total	50	100.0

Table B7 Frequency of SEo scores of output-orientated DEA

SEo scores	Frequency	Percent (%)
0.889	1	2.0
0.901	1	2.0
0.929	2	4.0
0.936	1	2.0
0.937	1	2.0
0.943	1	2.0
0.945	1	2.0
0.947	1	2.0
0.951	1	2.0
0.952	1	2.0
0.968	1	2.0
0.978	1	2.0
0.983	1	2.0
0.984	1	2.0
0.987	1	2.0
0.991	1	2.0
0.993	1	2.0
0.999	1	2.0
1	31	62.0
Total	50	100.0

Table B8 Compare CRSi vs. CRSo scores and education type by ranking

Ranking by descending CRSi and Edu. type scores			Ranking by descending CRSo and Edu. type scores		
Id.	CRSi	Edu. type	Id.	CRSo	Edu. type
1	1	1	1	1	1
2	1	3	2	1	3
3	1	3	3	1	3
4	1	1	4	1	1
5	1	3	5	1	3
8	1	1	8	1	1
10	1	3	10	1	3
11	1	3	11	1	3
12	1	1	12	1	1
13	1	2	13	1	2
17	1	3	17	1	3
20	1	1	20	1	1
23	1	3	23	1	3
27	1	3	27	1	3
28	1	3	28	1	3
29	1	1	29	1	1
30	1	3	30	1	3
32	1	3	32	1	3
33	1	1	33	1	1
35	1	3	35	1	3
36	1	3	36	1	3
37	1	1	37	1	1
38	1	2	38	1	2
39	1	2	39	1	2
42	1	3	42	1	3
43	1	3	43	1	3
45	1	1	45	1	1
46	1	3	46	1	3
47	1	2	47	1	2
48	1	3	48	1	3
50	1	2	50	1	2
9	0.977	1	9	0.977	1
26	0.951	1	26	0.951	1
7	0.945	3	7	0.945	3
25	0.943	1	25	0.943	1
49	0.922	1	49	0.922	1
34	0.915	1	34	0.915	1
41	0.912	3	41	0.912	3
40	0.908	2	40	0.908	2
18	0.905	3	18	0.905	3
31	0.901	1	31	0.901	1
16	0.896	3	16	0.896	3

6	0.889	1	6	0.889	1
14	0.887	2	14	0.887	2
21	0.877	3	21	0.877	3
44	0.858	1	44	0.858	1
24	0.855	1	24	0.855	1
19	0.851	1	19	0.851	1
15	0.85	2	15	0.85	2
22	0.81	1	22	0.81	1

Table B9 Compare VRSi vs. VRSo scores and education type by ranking

Ranking by descending VRSi and Edu. type scores			Ranking by descending VRSo and Edu. type scores		
Id.	VRSi	Edu. type	Id.	VRSo	Edu. type
1	1	1	1	1	1
2	1	3	2	1	3
3	1	3	3	1	3
4	1	1	4	1	1
5	1	3	5	1	3
6	1	1	6	1	1
7	1	3	7	1	3
8	1	1	8	1	1
10	1	3	10	1	3
11	1	3	11	1	3
12	1	1	12	1	1
13	1	2	13	1	2
17	1	3	17	1	3
20	1	1	20	1	1
23	1	3	23	1	3
25	1	1	25	1	1
26	1	1	26	1	1
27	1	3	27	1	3
28	1	3	28	1	3
29	1	1	29	1	1
30	1	3	30	1	3
31	1	1	31	1	1
32	1	3	32	1	3
33	1	1	33	1	1
35	1	3	35	1	3
36	1	3	36	1	3
37	1	1	37	1	1
38	1	2	38	1	2
39	1	2	39	1	2
42	1	3	42	1	3
43	1	3	43	1	3
45	1	1	45	1	1
46	1	3	46	1	3

47	1	2	47	1	2
48	1	3	48	1	3
50	1	2	50	1	2
24	0.994	1	49	0.985	1
49	0.993	1	9	0.984	1
14	0.989	2	41	0.974	3
9	0.985	1	14	0.954	2
41	0.982	3	16	0.946	3
16	0.966	3	18	0.925	3
44	0.954	1	40	0.923	2
18	0.947	3	24	0.92	1
19	0.942	1	34	0.916	1
34	0.926	1	19	0.894	1
40	0.908	2	21	0.892	3
21	0.903	3	44	0.886	1
15	0.854	2	15	0.862	2
22	0.811	1	22	0.817	1

Table B10 Compare SEi vs. SEo scores, pattern of scale inefficiency and education type by ranking

Ranking by descending SEi scores and Edu. type				Ranking by descending SEo scores and Edu. type			
Id.	SEi	RTSi	Edu. type	Id.	SEo	RTSo	Edu. type
1	1	-	1	1	1	-	1
2	1	-	3	2	1	-	3
3	1	-	3	3	1	-	3
4	1	-	1	4	1	-	1
5	1	-	3	5	1	-	3
8	1	-	1	8	1	-	1
10	1	-	3	10	1	-	3
11	1	-	3	11	1	-	3
12	1	-	1	12	1	-	1
13	1	-	2	13	1	-	2
17	1	-	3	17	1	-	3
20	1	-	1	20	1	-	1
23	1	-	3	23	1	-	3
27	1	-	3	27	1	-	3
28	1	-	3	28	1	-	3
29	1	-	1	29	1	-	1
30	1	-	3	30	1	-	3
32	1	-	3	32	1	-	3
33	1	-	1	33	1	-	1
35	1	-	3	35	1	-	3
36	1	-	3	36	1	-	3
37	1	-	1	37	1	-	1
38	1	-	2	38	1	-	2

39	1	-	2	39	1	-	2
40	1	-	2	42	1	-	3
42	1	-	3	43	1	-	3
43	1	-	3	45	1	-	1
45	1	-	1	46	1	-	3
46	1	-	3	47	1	-	2
47	1	-	2	48	1	-	3
48	1	-	3	50	1	-	2
50	1	-	2	34	0.999	drs	1
22	0.999	drs	1	9	0.993	irs	1
15	0.996	drs	2	22	0.991	drs	1
9	0.992	irs	1	15	0.987	drs	2
34	0.988	irs	1	40	0.984	drs	2
21	0.971	irs	3	21	0.983	irs	3
18	0.955	irs	3	18	0.978	irs	3
26	0.951	irs	1	44	0.968	irs	1
7	0.945	drs	3	19	0.952	irs	1
25	0.943	irs	1	26	0.951	irs	1
41	0.929	irs	3	16	0.947	irs	3
49	0.929	irs	1	7	0.945	drs	3
16	0.927	irs	3	25	0.943	irs	1
19	0.903	irs	1	41	0.937	irs	3
31	0.901	irs	1	49	0.936	irs	1
44	0.899	irs	1	14	0.929	irs	2
14	0.896	irs	2	24	0.929	irs	1
6	0.889	irs	1	31	0.901	irs	1
24	0.86	irs	1	6	0.889	irs	1

Appendix C Data of regression analysis

Table C1 Data of physician staffs and total physicians of regional hospitals

Hospitals No. (DMU)		Physician staffs		Practicing interns		Practicing refundable physicians		Practicing residents		Dentists		Total physicians	
2007	2008	2007	2008	2007	2008	2007	2008	2007	2008	2007	2008	2007	2008
1	26	65	72	15	10	0	0	0	0	10	11	90	93
2	27	88	111	22	15	14	6	5	7	10	12	139	151
3	28	146	143	19	18	33	32	42	48	22	20	262	261
4	29	63	72	12	14	0	0	0	0	10	12	85	98
5	30	99	100	23	20	20	18	20	18	9	10	171	166
6	31	40	43	7	10	0	0	0	0	7	8	54	61
7	32	175	186	40	30	19	20	10	18	18	21	262	275
8	33	56	62	24	20	0	0	0	0	10	9	90	91
9	34	67	73	24	14	0	0	0	0	12	13	103	100
10	35	120	133	46	34	0	4	1	1	12	14	179	186
11	36	121	117	39	30	42	45	22	20	21	20	245	232
12	37	95	110	35	27	0	0	0	0	14	15	144	152
13	38	99	99	21	25	19	18	0	0	12	12	151	154
14	39	67	74	19	18	16	13	0	0	9	9	111	114
15	40	84	84	16	22	0	8	0	0	11	12	111	126
16	41	97	107	23	19	13	16	2	2	12	11	147	155
17	42	115	124	31	32	34	36	11	14	13	16	204	222
18	43	85	91	10	10	15	17	4	4	9	10	123	132
19	44	60	64	17	12	0	0	0	0	12	11	89	87
20	45	89	91	20	12	0	0	0	0	15	15	124	118
21	46	80	84	10	29	5	5	1	3	11	12	107	133
22	47	85	89	13	18	2	4	0	0	11	9	111	120
23	48	110	116	18	22	26	34	17	13	16	18	187	203
24	49	57	55	10	12	0	0	0	0	12	12	79	79
25	50	40	45	8	12	0	0	0	0	6	7	54	64

Table C2 Data of in-patient visits, DRG and in-patient visits*DRG of regional hospitals

Hospitals No. (DMU)		In-patient visits		DRG		In-patient visits*DRG	
2007	2008	2007	2008	2007	2008	2007	2008
1	26	32563	35440	1.35	1.5	43960.05	53160
2	27	44453	45295	1.22	1.54	54232.66	69754.3
3	28	43427	45017	1.28	1.76	55586.56	79229.92
4	29	34345	39335	0.89	1.11	30567.05	43661.85
5	30	42285	41762	1.31	1.59	55393.35	66401.58
6	31	26268	27043	1.06	1.21	27844.08	32722.03
7	32	82545	85389	1.38	1.96	113912.1	167362.44
8	33	55261	56589	1.08	1.26	59681.88	71302.14
9	34	60449	62232	1.01	1.17	61053.49	72811.44
10	35	79360	81478	1.37	1.95	108723.2	158882.1
11	36	63810	66,630	1.5	1.92	95715	127929.6
12	37	66954	65,770	1.18	1.52	79005.72	99970.4
13	38	54559	56268	1.29	1.58	70381.11	88903.44
14	39	31115	40489	1.1	1.3	34226.5	52635.7
15	40	56709	58607	1.14	1.39	64648.26	81463.73
16	41	46820	48742	1.11	1.4	51970.2	68238.8
17	42	45198	48098	1.36	1.79	61469.28	86095.42
18	43	42242	44266	1.27	1.56	53647.34	69054.96
19	44	34840	38266	1.09	1.29	37975.6	49363.14
20	45	45804	49832	1.3	1.49	59545.2	74249.68
21	46	48401	49753	1.12	1.52	54209.12	75624.56
22	47	59359	58567	1	1.28	59359	74965.76
23	48	44567	47016	1.18	1.52	52589.06	71464.32
24	49	37953	40,840	0.87	0.98	33019.11	40023.2
25	50	22153	26544	1.12	1.33	24811.36	35303.52

Table C3 Descriptive statistics of physician staffs, in-patient visits and DRG

Descriptive statistics	Physician staffs	IPV	DRG
Numbers	50	50	50
Mean	90.96	49214.16	1.33
Standard deviation	31.98	14694.04	0.26
Minimum	40	22153	0.87
Maximum	186	85389	1.96
One-sample K-S test - Asymp. sig. (2-tailed)	0.826	0.433	0.776

Table C4 Dummy variables of regression analysis

Hospital No. (DMU)		U_j (near university hospital)		HA_j (pass hospital accreditation)	
2007	2008	2007	2008	2007	2008
1	26	0	0	1	1
2	27	0	0	1	1
3	28	1	1	1	1
4	29	0	0	0	1
5	30	0	0	1	1
6	31	0	0	1	0
7	32	0	0	0	0
8	33	0	0	0	0
9	34	0	0	1	1
10	35	0	0	1	0
11	36	1	1	1	0
12	37	0	0	1	1
13	38	0	0	1	0
14	39	0	0	1	1
15	40	0	0	1	1
16	41	0	0	1	0
17	42	1	1	1	1
18	43	0	0	1	1
19	44	0	0	0	1
20	45	0	0	1	0
21	46	0	0	0	1
22	47	0	0	1	0
23	48	1	1	1	1
24	49	0	0	1	0
25	50	0	0	1	1

Appendix D Results of regression analyses; the best & simplest models

Input-orientated measurement DEA; 50 DMUs in year 2007-2008

Table D1 Eviews' OLS estimation for TEVRS of input-orientated DEA

Dependent Variable: VRSI
Method: Least Squares
Sample: 1 50
Included observations: 50
VRSI=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS+C(8)
*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.193648	0.069300	17.22426	0.0000
C(2)	-0.027043	0.007445	-3.632140	0.0008
C(3)	-0.001455	0.000532	-2.737622	0.0090
C(4)	3.26E-06	1.47E-06	2.221315	0.0318
C(5)	0.018173	0.007865	2.310698	0.0258
C(6)	-0.008207	0.003486	-2.354063	0.0233
C(7)	0.182930	0.072182	2.534301	0.0151
C(8)	0.222389	0.164073	1.355429	0.1825

R-squared	0.380479	Mean dependent var	0.983080
Adjusted R-squared	0.277225	S.D. dependent var	0.039453
S.E. of regression	0.033542	Akaike info criterion	-3.806408
Sum squared resid	0.047252	Schwarz criterion	-3.500484
Log likelihood	103.1602	Hannan-Quinn criter.	-3.689911
F-statistic	3.684901	Durbin-Watson stat	1.915414
Prob(F-statistic)	0.003432		

Table D2 Eviews' OLS estimation for SE of input-orientated DEA

Dependent Variable: SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
SEI= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.897460	0.037869	23.69902	0.0000
C(2)	-4.34E-06	5.84E-06	-0.743358	0.4612
C(3)	0.000152	5.05E-05	3.013658	0.0043
C(4)	0.044599	0.043583	1.023312	0.3118
C(5)	0.036886	0.017574	2.098925	0.0416
C(6)	0.016369	0.011998	1.364226	0.1794

R-squared	0.230247	Mean dependent var	0.977460
Adjusted R-squared	0.142775	S.D. dependent var	0.038841
S.E. of regression	0.035961	Akaike info criterion	-3.700570
Sum squared resid	0.056902	Schwarz criterion	-3.471127
Log likelihood	98.51425	Hannan-Quinn criter.	-3.613197
F-statistic	2.632231	Durbin-Watson stat	2.039775
Prob(F-statistic)	0.036283		

Output-orientated measurement DEA; 50 DMUs in year 2007-2008

Table D3 Eviews' OLS estimation for TEVRS of output-orientated DEA

Dependent Variable: VRSO
Method: Least Squares
Sample: 1 50
Included observations: 50
VRSO=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS+C(8)
*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.136643	0.077642	14.63952	0.0000
C(2)	-0.029290	0.008342	-3.511322	0.0011
C(3)	-0.001107	0.000595	-1.859346	0.0700
C(4)	2.48E-06	1.64E-06	1.511116	0.1382
C(5)	0.023639	0.008811	2.682740	0.0104
C(6)	-0.008336	0.003906	-2.134202	0.0387
C(7)	0.208326	0.080870	2.576048	0.0136
C(8)	0.266873	0.183822	1.451801	0.1540

R-squared	0.372030	Mean dependent var	0.977560
Adjusted R-squared	0.267368	S.D. dependent var	0.043904
S.E. of regression	0.037579	Akaike info criterion	-3.579089
Sum squared resid	0.059312	Schwarz criterion	-3.273166
Log likelihood	97.47723	Hannan-Quinn criter.	-3.462592
F-statistic	3.554589	Durbin-Watson stat	2.075374
Prob(F-statistic)	0.004342		

Table D4 Eviews' OLS estimation for SE of output-orientated DEA

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.928444	0.028424	32.66435	0.0000
C(2)	-4.39E-06	4.38E-06	-1.000848	0.3224
C(3)	0.000110	3.79E-05	2.896914	0.0059
C(4)	0.033221	0.032712	1.015537	0.3154
C(5)	0.025174	0.013191	1.908459	0.0629
C(6)	0.014607	0.009006	1.622005	0.1119

R-squared	0.231005	Mean dependent var	0.982840
Adjusted R-squared	0.143619	S.D. dependent var	0.029168
S.E. of regression	0.026992	Akaike info criterion	-4.274389
Sum squared resid	0.032057	Schwarz criterion	-4.044946
Log likelihood	112.8597	Hannan-Quinn criter.	-4.187016
F-statistic	2.643502	Durbin-Watson stat	1.826792
Prob(F-statistic)	0.035650		

Appendix E Results of regression analyses; the alternative models

Input-orientated measurement DEA; 25 regional hospitals in year 2008

Table E1 Eviews' OLS estimation of TEVRS of input-orientated DEA for 25 regional hospitals in year 2008

Dependent Variable: VRSI
Method: Least Squares
Sample: 1 25
Included observations: 25
VRSI=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS+C(8)*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.053596	0.054499	19.33238	0.0000
C(2)	-0.010967	0.006292	-1.742941	0.0994
C(3)	-0.000368	0.000426	-0.862601	0.4004
C(4)	7.32E-07	1.13E-06	0.649979	0.5244
C(5)	0.010422	0.006465	1.612027	0.1254
C(6)	-0.003496	0.002452	-1.425809	0.1720
C(7)	0.044727	0.077759	0.575194	0.5727
C(8)	0.111574	0.115463	0.966317	0.3474

R-squared	0.233165	Mean dependent var	0.994280
Adjusted R-squared	-0.082591	S.D. dependent var	0.016410
S.E. of regression	0.017074	Akaike info criterion	-5.048138
Sum squared resid	0.004956	Schwarz criterion	-4.658097
Log likelihood	71.10172	Hannan-Quinn criter.	-4.939957
F-statistic	0.738434	Durbin-Watson stat	2.018337
Prob(F-statistic)	0.643297		

Table E2 Eviews' OLS estimation of SE of input-orientated DEA for 25 regional hospitals in year 2008

Dependent Variable: SEI
Method: Least Squares
Sample: 1 25
Included observations: 25
SEI= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.948120	0.046702	20.30157	0.0000
C(2)	-2.26E-06	5.97E-06	-0.378109	0.7095
C(3)	6.92E-05	5.68E-05	1.218846	0.2378
C(4)	0.044653	0.048569	0.919372	0.3694
C(5)	0.016583	0.019078	0.869238	0.3956
C(6)	0.005866	0.012179	0.481640	0.6356

R-squared	0.140770	Mean dependent var	0.987680
Adjusted R-squared	-0.085343	S.D. dependent var	0.026139
S.E. of regression	0.027231	Akaike info criterion	-4.163348
Sum squared resid	0.014089	Schwarz criterion	-3.870817
Log likelihood	58.04185	Hannan-Quinn criter.	-4.082212
F-statistic	0.622565	Durbin-Watson stat	2.131805
Prob(F-statistic)	0.684437		

Output-orientated DEA; 25 regional hospitals in year 2008

Table E3 Eviews' OLS estimation of TEVRS of output-orientated DEA for 25 regional hospitals in year 2008

Dependent Variable: VRSO
Method: Least Squares
Sample: 1 25
Included observations: 25
VRSO=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS+C(8)
*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.044127	0.078803	13.24989	0.0000
C(2)	-0.017007	0.009098	-1.869257	0.0789
C(3)	-0.000272	0.000617	-0.440498	0.6651
C(4)	4.19E-07	1.63E-06	0.257346	0.8000
C(5)	0.014958	0.009348	1.600105	0.1280
C(6)	-0.003059	0.003545	-0.862913	0.4002
C(7)	0.069263	0.112436	0.616027	0.5460
C(8)	0.152788	0.166954	0.915150	0.3729

R-squared	0.241960	Mean dependent var	0.990680
Adjusted R-squared	-0.070174	S.D. dependent var	0.023865
S.E. of regression	0.024689	Akaike info criterion	-4.310611
Sum squared resid	0.010362	Schwarz criterion	-3.920571
Log likelihood	61.88264	Hannan-Quinn criter.	-4.202430
F-statistic	0.775181	Durbin-Watson stat	2.407496
Prob(F-statistic)	0.616224		

Table E4 Eviews' OLS estimation of SE of output-orientated DEA for 25 regional hospitals in year 2008

Dependent Variable: SEO
Method: Least Squares
Sample: 1 25
Included observations: 25
SEO= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.950013	0.031045	30.60158	0.0000
C(2)	-3.08E-06	3.97E-06	-0.775608	0.4475
C(3)	7.62E-05	3.77E-05	2.019223	0.0578
C(4)	0.027037	0.032286	0.837422	0.4128
C(5)	0.013652	0.012682	1.076527	0.2952
C(6)	0.012023	0.008096	1.485047	0.1539

R-squared	0.257732	Mean dependent var	0.991320
Adjusted R-squared	0.062399	S.D. dependent var	0.018694
S.E. of regression	0.018102	Akaike info criterion	-4.980064
Sum squared resid	0.006226	Schwarz criterion	-4.687534
Log likelihood	68.25080	Hannan-Quinn criter.	-4.898929
F-statistic	1.319448	Durbin-Watson stat	1.944117
Prob(F-statistic)	0.297930		

The alternative models; 50 DMUs in year 2007-2008

Input-orientated DEA

- **TEVRSi**

Table E5 Eviews' OLS estimation for TEVRSi; alternative model 1

Dependent Variable: VRSI
Method: Least Squares
Sample: 1 50
Included observations: 50
VRSI=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.200797	0.069769	17.21108	0.0000
C(2)	-0.025892	0.007469	-3.466835	0.0012
C(3)	-0.001447	0.000537	-2.695651	0.0100
C(4)	3.52E-06	1.47E-06	2.403191	0.0206
C(5)	0.015210	0.007628	1.993935	0.0525
C(6)	-0.007521	0.003483	-2.159580	0.0364
C(7)	0.153019	0.069392	2.205159	0.0328

R-squared	0.353380	Mean dependent var	0.983080
Adjusted R-squared	0.263153	S.D. dependent var	0.039453
S.E. of regression	0.033867	Akaike info criterion	-3.803595
Sum squared resid	0.049319	Schwarz criterion	-3.535912
Log likelihood	102.0899	Hannan-Quinn criter.	-3.701660
F-statistic	3.916599	Durbin-Watson stat	1.891486
Prob(F-statistic)	0.003295		

Table E6 Eviews' OLS estimation for TEVRSi; alternative model 2

Dependent Variable: VRSI
Method: Least Squares
Sample: 1 50
Included observations: 50
VRSI=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(6)*OPP+C(7)*IPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.193034	0.071977	16.57517	0.0000
C(2)	-0.016473	0.005977	-2.755985	0.0085
C(3)	-0.001496	0.000554	-2.700311	0.0098
C(4)	3.76E-06	1.51E-06	2.491213	0.0166
C(6)	-0.003411	0.002901	-1.176022	0.2459
C(7)	0.150593	0.071689	2.100657	0.0414

R-squared	0.293593	Mean dependent var	0.983080
Adjusted R-squared	0.213320	S.D. dependent var	0.039453
S.E. of regression	0.034993	Akaike info criterion	-3.755163
Sum squared resid	0.053879	Schwarz criterion	-3.525721
Log likelihood	99.87908	Hannan-Quinn criter.	-3.667790
F-statistic	3.657408	Durbin-Watson stat	1.914517
Prob(F-statistic)	0.007462		

Table E7 Eviews' OLS estimation for TEVRSi; alternative model 3

Dependent Variable: VRSI
Method: Least Squares
Sample: 1 50
Included observations: 50
VRSI=C(1)+C(2)*BP+C(3)*P+C(5)*NP+C(6)*OPP+C(7)*IPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.084526	0.052926	20.49147	0.0000
C(2)	-0.023316	0.007782	-2.996184	0.0045
C(3)	-0.000201	0.000147	-1.372016	0.1770
C(5)	0.016702	0.008005	2.086577	0.0428
C(6)	-0.006440	0.003636	-1.771189	0.0835
C(7)	0.116420	0.071279	1.633307	0.1095

R-squared	0.266532	Mean dependent var	0.983080
Adjusted R-squared	0.183183	S.D. dependent var	0.039453
S.E. of regression	0.035657	Akaike info criterion	-3.717571
Sum squared resid	0.055943	Schwarz criterion	-3.488128
Log likelihood	98.93927	Hannan-Quinn criter.	-3.630198
F-statistic	3.197796	Durbin-Watson stat	1.546943
Prob(F-statistic)	0.015074		

Table E8 Eviews' OLS estimation for TEVRSi; alternative model 4

Dependent Variable: VRSI
Method: Least Squares
Sample: 1 50
Included observations: 50
VRSI=C(1)+C(2)*BP+C(3)*P+C(5)*NP+C(6)*OPP+C(7)*IPS+C(8)*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.086601	0.052030	20.88422	0.0000
C(2)	-0.024961	0.007717	-3.234647	0.0023
C(3)	-0.000327	0.000164	-1.992583	0.0527
C(5)	0.020183	0.008162	2.472684	0.0174
C(6)	-0.007378	0.003621	-2.037372	0.0478
C(7)	0.156349	0.074368	2.102362	0.0414
C(8)	0.271582	0.169846	1.598995	0.1171

R-squared	0.307696	Mean dependent var	0.983080
Adjusted R-squared	0.211096	S.D. dependent var	0.039453
S.E. of regression	0.035043	Akaike info criterion	-3.735330
Sum squared resid	0.052803	Schwarz criterion	-3.467647
Log likelihood	100.3833	Hannan-Quinn criter.	-3.633395
F-statistic	3.185247	Durbin-Watson stat	1.659992
Prob(F-statistic)	0.011243		

- **SEi**

Table E9 Eviews' OLS estimation for SEi; alternative model 1

Dependent Variable: SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
SEI= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*OP*UJ+C(7)
*IDRGP*UJ +C(8)*MPS*UJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.890632	0.041845	21.28415	0.0000
C(2)	-1.65E-06	6.19E-06	-0.266403	0.7912
C(3)	0.000159	5.40E-05	2.937392	0.0054
C(4)	0.075969	0.055142	1.377705	0.1756
C(5)	0.109368	0.211662	0.516708	0.6081
C(6)	1.65E-06	9.81E-05	0.016808	0.9867
C(7)	-0.000159	0.000190	-0.836706	0.4075
C(8)	-0.075969	0.212439	-0.357606	0.7224

R-squared	0.227250	Mean dependent var	0.977460
Adjusted R-squared	0.098459	S.D. dependent var	0.038841
S.E. of regression	0.036879	Akaike info criterion	-3.616685
Sum squared resid	0.057124	Schwarz criterion	-3.310761
Log likelihood	98.41713	Hannan-Quinn criter.	-3.500188
F-statistic	1.764481	Durbin-Watson stat	2.172150
Prob(F-statistic)	0.120259		

Table E10 Eviews' OLS estimation for SEi; alternative model 2

Dependent Variable: SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
SEI= C(1)+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(7)*IDRGP*UJ +C(8)*MPS*UJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.883148	0.030324	29.12342	0.0000
C(3)	0.000158	5.28E-05	3.001311	0.0044
C(4)	0.080685	0.051065	1.580050	0.1213
C(5)	0.116852	0.059056	1.978677	0.0541
C(7)	-0.000158	0.000146	-1.087582	0.2827
C(8)	-0.080685	0.098615	-0.818187	0.4177

R-squared	0.225945	Mean dependent var	0.977460
Adjusted R-squared	0.137984	S.D. dependent var	0.038841
S.E. of regression	0.036062	Akaike info criterion	-3.694997
Sum squared resid	0.057220	Schwarz criterion	-3.465554
Log likelihood	98.37492	Hannan-Quinn criter.	-3.607624
F-statistic	2.568694	Durbin-Watson stat	2.180849
Prob(F-statistic)	0.040068		

Table E11 Eviews' OLS estimation for SEi; alternative model 3

Dependent Variable: SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
SEI= C(1)+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(7)*IDRGP*UJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.889967	0.029049	30.63657	0.0000
C(3)	0.000149	5.13E-05	2.902911	0.0057
C(4)	0.059050	0.043525	1.356706	0.1816
C(5)	0.099653	0.054985	1.812377	0.0766
C(7)	-0.000162	0.000145	-1.116082	0.2703

R-squared	0.214168	Mean dependent var	0.977460
Adjusted R-squared	0.144316	S.D. dependent var	0.038841
S.E. of regression	0.035929	Akaike info criterion	-3.719897
Sum squared resid	0.058091	Schwarz criterion	-3.528695
Log likelihood	97.99743	Hannan-Quinn criter.	-3.647086
F-statistic	3.066034	Durbin-Watson stat	2.120910
Prob(F-statistic)	0.025689		

Table E12 Eviews' OLS estimation for SEi; alternative model 4

Dependent Variable: SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
SEI= C(1)+C(3)*IDRGP+C(4)*MPS+C(5)*UJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.902150	0.026992	33.42271	0.0000
C(3)	0.000127	4.76E-05	2.672732	0.0104
C(4)	0.049459	0.042782	1.156074	0.2536
C(5)	0.041138	0.016612	2.476334	0.0170

R-squared	0.192415	Mean dependent var	0.977460
Adjusted R-squared	0.139747	S.D. dependent var	0.038841
S.E. of regression	0.036025	Akaike info criterion	-3.732592
Sum squared resid	0.059699	Schwarz criterion	-3.579631
Log likelihood	97.31481	Hannan-Quinn criter.	-3.674344
F-statistic	3.653323	Durbin-Watson stat	2.108753
Prob(F-statistic)	0.019131		

Table E13 Eviews' OLS estimation for SEi; alternative model 5

Dependent Variable: SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
SEI= C(1)+C(3)*IDRGP+C(5)*UJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.915823	0.024350	37.61123	0.0000
C(3)	0.000109	4.52E-05	2.419348	0.0195
C(5)	0.046203	0.016081	2.873113	0.0061

R-squared	0.168951	Mean dependent var	0.977460
Adjusted R-squared	0.133588	S.D. dependent var	0.038841
S.E. of regression	0.036154	Akaike info criterion	-3.743952
Sum squared resid	0.061433	Schwarz criterion	-3.629231
Log likelihood	96.59880	Hannan-Quinn criter.	-3.700265
F-statistic	4.777525	Durbin-Watson stat	2.152163
Prob(F-statistic)	0.012919		

Table E14 Eviews' OLS estimation for SEi; alternative model 6

Dependent Variable: SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
SEI=C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*HAJ+C(6)*OP*HAJ+C(7)
*IDRGP*HAJ+C(8)*MPS*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.855799	0.071743	11.92861	0.0000
C(2)	2.60E-06	1.09E-05	0.239198	0.8121
C(3)	0.000171	7.73E-05	2.206085	0.0329
C(4)	0.106097	0.117050	0.906418	0.3699
C(5)	0.114928	0.081103	1.417060	0.1638
C(6)	-1.47E-05	1.32E-05	-1.115282	0.2711
C(7)	-5.78E-05	0.000106	-0.544917	0.5887
C(8)	-0.054317	0.127422	-0.426276	0.6721

R-squared	0.188048	Mean dependent var	0.977460
Adjusted R-squared	0.052723	S.D. dependent var	0.038841
S.E. of regression	0.037803	Akaike info criterion	-3.567200
Sum squared resid	0.060021	Schwarz criterion	-3.261276
Log likelihood	97.17999	Hannan-Quinn criter.	-3.450702
F-statistic	1.389603	Durbin-Watson stat	2.112212
Prob(F-statistic)	0.235054		

Table E15 Eviews' OLS estimation for SEi; alternative model 7

Dependent Variable: SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
SEI=C(1)+C(3)*IDRGP+C(4)*MPS+C(5)*HAJ+C(6)*OP*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.887705	0.031895	27.83173	0.0000
C(3)	0.000139	5.13E-05	2.717521	0.0093
C(4)	0.063946	0.042760	1.495448	0.1418
C(5)	0.073381	0.032560	2.253709	0.0291
C(6)	-1.32E-05	6.81E-06	-1.932980	0.0595

R-squared	0.180579	Mean dependent var	0.977460
Adjusted R-squared	0.107741	S.D. dependent var	0.038841
S.E. of regression	0.036689	Akaike info criterion	-3.678042
Sum squared resid	0.060574	Schwarz criterion	-3.486840
Log likelihood	96.95105	Hannan-Quinn criter.	-3.605231
F-statistic	2.479200	Durbin-Watson stat	2.103531
Prob(F-statistic)	0.057322		

Table E16 Eviews' OLS estimation for SEi; alternative model 8

Dependent Variable: SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
SEI=C(1)+C(3)*IDRGP+C(5)*HAJ+C(6)*OP*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.908223	0.029178	31.12689	0.0000
C(3)	0.000112	4.86E-05	2.309808	0.0254
C(5)	0.081063	0.032582	2.487973	0.0165
C(6)	-1.50E-05	6.78E-06	-2.212905	0.0319

R-squared	0.139856	Mean dependent var	0.977460
Adjusted R-squared	0.083759	S.D. dependent var	0.038841
S.E. of regression	0.037179	Akaike info criterion	-3.669540
Sum squared resid	0.063584	Schwarz criterion	-3.516578
Log likelihood	95.73851	Hannan-Quinn criter.	-3.611292
F-statistic	2.493135	Durbin-Watson stat	2.171748
Prob(F-statistic)	0.071775		

Table E17 Eviews' OLS estimation for SEi; alternative model 9

Dependent Variable: SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
SEI= C(1)+C(2)*IDRGP+C(3)*UJ+C(4)*HAJ+C(5)*OP*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.887200	0.029666	29.90601	0.0000
C(2)	0.000145	4.91E-05	2.952774	0.0050
C(3)	0.037840	0.017355	2.180398	0.0345
C(4)	0.053722	0.033745	1.592012	0.1184
C(5)	-8.80E-06	7.12E-06	-1.235604	0.2230

R-squared	0.222045	Mean dependent var	0.977460
Adjusted R-squared	0.152893	S.D. dependent var	0.038841
S.E. of regression	0.035749	Akaike info criterion	-3.729971
Sum squared resid	0.057508	Schwarz criterion	-3.538769
Log likelihood	98.24928	Hannan-Quinn criter.	-3.657160
F-statistic	3.210986	Durbin-Watson stat	2.143149
Prob(F-statistic)	0.021103		

Table E18 Eviews' OLS estimation for SEi; alternative model 10

Dependent Variable: SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
SEI= C(1)+C(2)*IDRGP+C(3)*UJ+C(4)*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.896349	0.028891	31.02482	0.0000
C(2)	0.000128	4.73E-05	2.698723	0.0097
C(3)	0.046428	0.015993	2.903018	0.0057
C(4)	0.014656	0.011861	1.235692	0.2228

R-squared	0.195651	Mean dependent var	0.977460
Adjusted R-squared	0.143194	S.D. dependent var	0.038841
S.E. of regression	0.035953	Akaike info criterion	-3.736607
Sum squared resid	0.059459	Schwarz criterion	-3.583645
Log likelihood	97.41518	Hannan-Quinn criter.	-3.678358
F-statistic	3.729703	Durbin-Watson stat	2.110045
Prob(F-statistic)	0.017564		

Output-orientated DEA

- **TEVRSo**

Table E19 Eviews' OLS estimation for TEVRSo; alternative model 1

Dependent Variable: VRSO
Method: Least Squares
Sample: 1 50
Included observations: 50
VRSO=C(1)+C(2)*BP+C(3)*P+C(5)*NP+C(6)*OPP+C(7)*IPS+C(8)*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.055055	0.056623	18.63313	0.0000
C(2)	-0.027703	0.008398	-3.298851	0.0020
C(3)	-0.000248	0.000179	-1.385489	0.1730
C(5)	0.025170	0.008883	2.833646	0.0070
C(6)	-0.007704	0.003941	-1.954899	0.0571
C(7)	0.188066	0.080933	2.323735	0.0249
C(8)	0.304367	0.184838	1.646665	0.1069

R-squared	0.337888	Mean dependent var	0.977560
Adjusted R-squared	0.245500	S.D. dependent var	0.043904
S.E. of regression	0.038136	Akaike info criterion	-3.566147
Sum squared resid	0.062537	Schwarz criterion	-3.298464
Log likelihood	96.15369	Hannan-Quinn criter.	-3.464212
F-statistic	3.657278	Durbin-Watson stat	1.846816
Prob(F-statistic)	0.005068		

Table E20 Eviews' OLS estimation for TEVRSo; alternative model 2

Dependent Variable: VRSO
Method: Least Squares
Sample: 1 50
Included observations: 50
VRSO=C(1)+C(2)*BP+C(5)*NP+C(6)*OPP+C(7)*IPS+C(8)*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.994227	0.036129	27.51869	0.0000
C(2)	-0.021077	0.006975	-3.021899	0.0042
C(5)	0.022277	0.008723	2.553700	0.0142
C(6)	-0.006228	0.003834	-1.624604	0.1114
C(7)	0.163383	0.079768	2.048218	0.0465
C(8)	0.181341	0.163798	1.107104	0.2743

R-squared	0.308330	Mean dependent var	0.977560
Adjusted R-squared	0.229731	S.D. dependent var	0.043904
S.E. of regression	0.038532	Akaike info criterion	-3.562474
Sum squared resid	0.065328	Schwarz criterion	-3.333031
Log likelihood	95.06184	Hannan-Quinn criter.	-3.475101
F-statistic	3.922833	Durbin-Watson stat	1.853868
Prob(F-statistic)	0.005000		

Table E21 Eviews' OLS estimation for TEVRSo; alternative model 3

Dependent Variable: VRSO
Method: Least Squares
Sample: 1 50
Included observations: 50
VRSO=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.145222	0.078408	14.60598	0.0000
C(2)	-0.027909	0.008393	-3.325191	0.0018
C(3)	-0.001097	0.000603	-1.819008	0.0759
C(4)	2.80E-06	1.65E-06	1.701071	0.0962
C(5)	0.020083	0.008572	2.342687	0.0238
C(6)	-0.007513	0.003914	-1.919593	0.0616
C(7)	0.172432	0.077984	2.211124	0.0324

R-squared	0.340515	Mean dependent var	0.977560
Adjusted R-squared	0.248494	S.D. dependent var	0.043904
S.E. of regression	0.038060	Akaike info criterion	-3.570124
Sum squared resid	0.062289	Schwarz criterion	-3.302441
Log likelihood	96.25310	Hannan-Quinn criter.	-3.468189
F-statistic	3.700407	Durbin-Watson stat	2.023787
Prob(F-statistic)	0.004716		

Table E22 Eviews' OLS estimation for TEVRSo; alternative model 4

Dependent Variable: VRSO
Method: Least Squares
Sample: 1 50
Included observations: 50
VRSO=C(1)+C(2)*BP+C(3)*P+C(5)*NP+C(6)*OPP+C(7)*IPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.052730	0.057695	18.24636	0.0000
C(2)	-0.025860	0.008483	-3.048376	0.0039
C(3)	-0.000106	0.000160	-0.664957	0.5095
C(5)	0.021270	0.008726	2.437548	0.0189
C(6)	-0.006653	0.003964	-1.678519	0.1003
C(7)	0.143318	0.077702	1.844444	0.0719

R-squared	0.296136	Mean dependent var	0.977560
Adjusted R-squared	0.216152	S.D. dependent var	0.043904
S.E. of regression	0.038870	Akaike info criterion	-3.544997
Sum squared resid	0.066480	Schwarz criterion	-3.315555
Log likelihood	94.62494	Hannan-Quinn criter.	-3.457624
F-statistic	3.702417	Durbin-Watson stat	1.714487
Prob(F-statistic)	0.006971		

Table E23 Eviews' OLS estimation for TEVRSo; alternative model 5

Dependent Variable: VRSO
Method: Least Squares
Sample: 1 50
Included observations: 50
VRSO=C(1)+C(2)*BP+C(5)*NP+C(6)*OPP+C(7)*IPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.019327	0.028201	36.14480	0.0000
C(2)	-0.022580	0.006859	-3.292179	0.0019
C(5)	0.020536	0.008602	2.387310	0.0212
C(6)	-0.006067	0.003841	-1.579756	0.1212
C(7)	0.139639	0.077023	1.812940	0.0765

R-squared	0.289063	Mean dependent var	0.977560
Adjusted R-squared	0.225868	S.D. dependent var	0.043904
S.E. of regression	0.038629	Akaike info criterion	-3.574998
Sum squared resid	0.067148	Schwarz criterion	-3.383796
Log likelihood	94.37496	Hannan-Quinn criter.	-3.502187
F-statistic	4.574182	Durbin-Watson stat	1.740339
Prob(F-statistic)	0.003479		

Table E24 Eviews' OLS estimation for TEVRSo; alternative model 6

Dependent Variable: VRSO
Method: Least Squares
Sample: 1 50
Included observations: 50
VRSO=C(1)+C(2)*BP+C(5)*NP+C(7)*IPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.003785	0.026856	37.37674	0.0000
C(2)	-0.021812	0.006952	-3.137585	0.0030
C(5)	0.012367	0.006985	1.770453	0.0833
C(7)	0.148179	0.078072	1.897975	0.0640

R-squared	0.249635	Mean dependent var	0.977560
Adjusted R-squared	0.200698	S.D. dependent var	0.043904
S.E. of regression	0.039252	Akaike info criterion	-3.561023
Sum squared resid	0.070872	Schwarz criterion	-3.408061
Log likelihood	93.02558	Hannan-Quinn criter.	-3.502774
F-statistic	5.101174	Durbin-Watson stat	1.691189
Prob(F-statistic)	0.003938		

- **SEo**

Table E25 Eviews' OLS estimation for SEi; alternative model 1

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*OP*UJ +C(7)
*IDRGP*UJ +C(8)*MPS*UJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.927352	0.031778	29.18190	0.0000
C(2)	-2.29E-06	4.70E-06	-0.488173	0.6280
C(3)	0.000110	4.10E-05	2.672872	0.0107
C(4)	0.054878	0.041876	1.310476	0.1972
C(5)	0.072648	0.160743	0.451954	0.6536
C(6)	2.29E-06	7.45E-05	0.030800	0.9756
C(7)	-0.000110	0.000144	-0.761358	0.4507
C(8)	-0.054878	0.161333	-0.340155	0.7354

R-squared	0.209695	Mean dependent var	0.982840
Adjusted R-squared	0.077978	S.D. dependent var	0.029168
S.E. of regression	0.028007	Akaike info criterion	-4.167056
Sum squared resid	0.032945	Schwarz criterion	-3.861132
Log likelihood	112.1764	Hannan-Quinn criter.	-4.050558
F-statistic	1.592010	Durbin-Watson stat	1.987585
Prob(F-statistic)	0.164421		

Table E26 Eviews' OLS estimation for SEi; alternative model 2

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(7)*IDRGP*UJ
+C(8)*MPS*UJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.927310	0.031379	29.55213	0.0000
C(2)	-2.29E-06	4.64E-06	-0.492961	0.6245
C(3)	0.000110	4.05E-05	2.704455	0.0098
C(4)	0.054904	0.041379	1.326874	0.1916
C(5)	0.077380	0.046773	1.654379	0.1053
C(7)	-0.000107	0.000112	-0.954598	0.3451
C(8)	-0.050559	0.078847	-0.641227	0.5248

R-squared	0.209678	Mean dependent var	0.982840
Adjusted R-squared	0.099400	S.D. dependent var	0.029168
S.E. of regression	0.027680	Akaike info criterion	-4.207033
Sum squared resid	0.032946	Schwarz criterion	-3.939350
Log likelihood	112.1758	Hannan-Quinn criter.	-4.105098
F-statistic	1.901363	Durbin-Watson stat	1.987471
Prob(F-statistic)	0.102506		

Table E27 Eviews' OLS estimation for SEi; alternative model 3

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO= C(1)+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(7)*IDRGP*UJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.922129	0.022105	41.71597	0.0000
C(3)	0.000102	3.90E-05	2.616432	0.0121
C(4)	0.044966	0.033120	1.357676	0.1813
C(5)	0.069967	0.041840	1.672228	0.1014
C(7)	-0.000112	0.000110	-1.014827	0.3156

R-squared	0.193101	Mean dependent var	0.982840
Adjusted R-squared	0.121377	S.D. dependent var	0.029168
S.E. of regression	0.027340	Akaike info criterion	-4.266276
Sum squared resid	0.033637	Schwarz criterion	-4.075074
Log likelihood	111.6569	Hannan-Quinn criter.	-4.193465
F-statistic	2.692273	Durbin-Watson stat	1.985626
Prob(F-statistic)	0.042791		

Table E28 Eviews' OLS estimation for SEi; alternative model 4

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO= C(1)+C(3)*IDRGP+C(4)*MPS+C(5)*UJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.930558	0.020492	45.41158	0.0000
C(3)	8.72E-05	3.62E-05	2.410978	0.0200
C(4)	0.038330	0.032479	1.180157	0.2440
C(5)	0.029479	0.012612	2.337485	0.0238

R-squared	0.174635	Mean dependent var	0.982840
Adjusted R-squared	0.120807	S.D. dependent var	0.029168
S.E. of regression	0.027349	Akaike info criterion	-4.283648
Sum squared resid	0.034407	Schwarz criterion	-4.130686
Log likelihood	111.0912	Hannan-Quinn criter.	-4.225399
F-statistic	3.244299	Durbin-Watson stat	1.957245
Prob(F-statistic)	0.030342		

Table E29 Eviews' OLS estimation for SEi; alternative model 5

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO= C(1)+C(3)*IDRGP+C(5)*UJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.941155	0.018497	50.88259	0.0000
C(3)	7.32E-05	3.43E-05	2.133706	0.0381
C(5)	0.033405	0.012216	2.734616	0.0088

R-squared	0.149645	Mean dependent var	0.982840
Adjusted R-squared	0.113459	S.D. dependent var	0.029168
S.E. of regression	0.027463	Akaike info criterion	-4.293819
Sum squared resid	0.035449	Schwarz criterion	-4.179098
Log likelihood	110.3455	Hannan-Quinn criter.	-4.250133
F-statistic	4.135503	Durbin-Watson stat	2.017444
Prob(F-statistic)	0.022162		

Table E30 Eviews' OLS estimation for SEi; alternative model 6

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO=C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*HAJ+C(6)*OP*HAJ+C(7)
*IDRGP*HAJ+C(8)*MPS*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.892521	0.053240	16.76418	0.0000
C(2)	1.26E-06	8.07E-06	0.156067	0.8767
C(3)	0.000129	5.74E-05	2.257033	0.0293
C(4)	0.071328	0.086861	0.821174	0.4162
C(5)	0.091784	0.060185	1.525025	0.1347
C(6)	-1.13E-05	9.80E-06	-1.150728	0.2564
C(7)	-4.90E-05	7.87E-05	-0.622605	0.5369
C(8)	-0.033135	0.094558	-0.350418	0.7278

R-squared	0.207103	Mean dependent var	0.982840
Adjusted R-squared	0.074953	S.D. dependent var	0.029168
S.E. of regression	0.028053	Akaike info criterion	-4.163780
Sum squared resid	0.033053	Schwarz criterion	-3.857857
Log likelihood	112.0945	Hannan-Quinn criter.	-4.047283
F-statistic	1.567185	Durbin-Watson stat	1.892458
Prob(F-statistic)	0.171899		

Table E31 Eviews' OLS estimation for SEi; alternative model 7

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO=C(1)+C(3)*IDRGP+C(4)*MPS+C(5)*HAJ+C(6)*OP*HAJ+C(7)*IDRGP
*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.902384	0.032265	27.96753	0.0000
C(3)	0.000125	5.49E-05	2.282381	0.0274
C(4)	0.043454	0.032680	1.329690	0.1905
C(5)	0.079391	0.039456	2.012168	0.0503
C(6)	-9.93E-06	5.43E-06	-1.830109	0.0740
C(7)	-4.15E-05	7.40E-05	-0.561063	0.5776

R-squared	0.204782	Mean dependent var	0.982840
Adjusted R-squared	0.114417	S.D. dependent var	0.029168
S.E. of regression	0.027448	Akaike info criterion	-4.240858
Sum squared resid	0.033150	Schwarz criterion	-4.011415
Log likelihood	112.0215	Hannan-Quinn criter.	-4.153485
F-statistic	2.266154	Durbin-Watson stat	1.886065
Prob(F-statistic)	0.064298		

Table E32 Eviews' OLS estimation for SEi; alternative model 8

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO=C(1)+C(3)*IDRGP+C(4)*MPS+C(5)*HAJ+C(6)*OP*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.914569	0.023680	38.62247	0.0000
C(3)	0.000103	3.81E-05	2.713036	0.0094
C(4)	0.047199	0.031746	1.486771	0.1440
C(5)	0.061977	0.024173	2.563860	0.0138
C(6)	-1.10E-05	5.05E-06	-2.173221	0.0351

R-squared	0.199093	Mean dependent var	0.982840
Adjusted R-squared	0.127901	S.D. dependent var	0.029168
S.E. of regression	0.027239	Akaike info criterion	-4.273729
Sum squared resid	0.033387	Schwarz criterion	-4.082527
Log likelihood	111.8432	Hannan-Quinn criter.	-4.200918
F-statistic	2.796578	Durbin-Watson stat	1.876915
Prob(F-statistic)	0.037097		

Table E33 Eviews' OLS estimation for SEi; alternative model 9

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO=C(1)+C(3)*IDRGP+C(5)*HAJ+C(6)*OP*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.929714	0.021656	42.93026	0.0000
C(3)	8.33E-05	3.61E-05	2.308936	0.0255
C(5)	0.067647	0.024183	2.797318	0.0075
C(6)	-1.24E-05	5.04E-06	-2.453092	0.0180

R-squared	0.159751	Mean dependent var	0.982840
Adjusted R-squared	0.104952	S.D. dependent var	0.029168
S.E. of regression	0.027595	Akaike info criterion	-4.265776
Sum squared resid	0.035027	Schwarz criterion	-4.112814
Log likelihood	110.6444	Hannan-Quinn criter.	-4.207527
F-statistic	2.915227	Durbin-Watson stat	1.961213
Prob(F-statistic)	0.044156		

Table E34 Eviews' OLS estimation for SEi; alternative model 10

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO= C(1)+C(2)*IDRGP+C(3)*UJ+C(4)*MPS+C(5)*HAJ+C(6)*OP*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.905734	0.023776	38.09510	0.0000
C(2)	0.000118	3.83E-05	3.079678	0.0036
C(3)	0.022507	0.013255	1.697984	0.0966
C(4)	0.035762	0.031823	1.123789	0.2672
C(5)	0.047089	0.025254	1.864603	0.0689
C(6)	-7.62E-06	5.33E-06	-1.428263	0.1603

R-squared	0.248346	Mean dependent var	0.982840
Adjusted R-squared	0.162931	S.D. dependent var	0.029168
S.E. of regression	0.026686	Akaike info criterion	-4.297198
Sum squared resid	0.031334	Schwarz criterion	-4.067755
Log likelihood	113.4299	Hannan-Quinn criter.	-4.209825
F-statistic	2.907517	Durbin-Watson stat	1.911390
Prob(F-statistic)	0.023627		

Table E35 Eviews' OLS estimation for SEi; alternative model 11

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO= C(1)+C(2)*IDRGP+C(3)*UJ+C(5)*HAJ+C(6)*OP*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.915457	0.022210	41.21810	0.0000
C(2)	0.000105	3.67E-05	2.869548	0.0062
C(3)	0.025660	0.012993	1.974957	0.0544
C(5)	0.049106	0.025264	1.943765	0.0582
C(6)	-8.14E-06	5.33E-06	-1.526626	0.1339

R-squared	0.226772	Mean dependent var	0.982840
Adjusted R-squared	0.158041	S.D. dependent var	0.029168
S.E. of regression	0.026764	Akaike info criterion	-4.308900
Sum squared resid	0.032233	Schwarz criterion	-4.117698
Log likelihood	112.7225	Hannan-Quinn criter.	-4.236089
F-statistic	3.299395	Durbin-Watson stat	1.989878
Prob(F-statistic)	0.018725		

Table E36 Eviews' OLS estimation for SEi; alternative model 12

Dependent Variable: SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
SEO= C(1)+C(2)*IDRGP+C(3)*UJ+C(5)*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.923920	0.021816	42.35063	0.0000
C(2)	8.96E-05	3.57E-05	2.505571	0.0158
C(3)	0.033604	0.012076	2.782622	0.0078
C(5)	0.012970	0.008956	1.448231	0.1543

R-squared	0.186726	Mean dependent var	0.982840
Adjusted R-squared	0.133686	S.D. dependent var	0.029168
S.E. of regression	0.027148	Akaike info criterion	-4.298406
Sum squared resid	0.033903	Schwarz criterion	-4.145444
Log likelihood	111.4601	Hannan-Quinn criter.	-4.240157
F-statistic	3.520498	Durbin-Watson stat	1.982322
Prob(F-statistic)	0.022207		

Appendix F Detection of the problems of multicollinearity and heteroscedasticity

Table F1 Eviews' estimation for correlation of explanatory variables of TEVRS scores (detection of the problems of multicollinearity)

	BP	P	P2	NP	OPP	IPS	RPS
BP	1.000000	-0.791973	-0.741554	0.846116	0.644816	0.038766	-0.558944
P	-0.791973	1.000000	0.981723	-0.676335	-0.600462	0.022042	0.652667
P2	-0.741554	0.981723	1.000000	-0.613629	-0.541156	-0.015580	0.660041
NP	0.846116	-0.676335	-0.613629	1.000000	0.791967	-0.013887	-0.546995
OPP	0.644816	-0.600462	-0.541156	0.791967	1.000000	-0.058024	-0.397021
IPS	0.038766	0.022042	-0.015580	-0.013887	-0.058024	1.000000	-0.230572
RPS	-0.558944	0.652667	0.660041	-0.546995	-0.397021	-0.230572	1.000000

Table F2 Eviews' estimation for correlation of explanatory variables of SE scores (detection of the problems of multicollinearity)

	OP	IDRGP	MPS	UJ	HAJ
OP	1.000000	0.372690	-0.403415	-0.489289	-0.007748
IDRGP	0.372690	1.000000	-0.473131	-0.497865	-0.353267
MPS	-0.403415	-0.473131	1.000000	0.437085	0.142080
UJ	-0.489289	-0.497865	0.437085	1.000000	0.166667
HAJ	-0.007748	-0.353267	0.142080	0.166667	1.000000

Table F3 Eviews' estimation for Residual test/ White heteroskedasticity test including White cross term of explanatory variables of TEVRSi scores (detection of the problems of heteroscedasticity)

Heteroskedasticity Test: White

F-statistic	1.291964	Prob. F(34,15)	0.3047
Obs*R-squared	37.27234	Prob. Chi-Square(34)	0.3209
Scaled explained SS	88.14093	Prob. Chi-Square(34)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample: 1 50
Included observations: 50
Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.152877	0.185953	-0.822128	0.4239
BP	0.006570	0.019997	0.328563	0.7470
BP^2	-0.002203	0.002400	-0.917873	0.3732
BP*P	-6.13E-05	0.000191	-0.321262	0.7524
BP*P2	2.16E-07	8.02E-07	0.269754	0.7910
BP*NP	0.002496	0.003937	0.633935	0.5357
BP*OPP	0.001154	0.000861	1.340635	0.2000
BP*IPS	-0.001561	0.015199	-0.102711	0.9196
BP*RPS	-0.035618	0.204152	-0.174466	0.8638
P	0.002996	0.003793	0.789930	0.4419
P^2	-2.76E-05	3.28E-05	-0.841727	0.4132
P*P2	1.13E-07	1.27E-07	0.891680	0.3866
P*NP	-0.000294	0.000252	-1.164502	0.2624

P*OPP	0.000186	0.000112	1.661972	0.1173
P*IPS	-0.001275	0.001714	-0.743602	0.4686
P*RPS	-0.029180	0.038439	-0.759116	0.4595
P2^2	-1.73E-10	1.91E-10	-0.908408	0.3780
P2*NP	1.07E-06	9.81E-07	1.089714	0.2930
P2*OPP	-5.93E-07	5.25E-07	-1.129254	0.2765
P2*IPS	1.18E-06	6.27E-06	0.188102	0.8533
P2*RPS	6.63E-05	8.90E-05	0.745226	0.4677
NP	0.020849	0.024375	0.855347	0.4058
NP^2	-0.001287	0.001654	-0.778212	0.4485
NP*OPP	-0.000575	0.000884	-0.650897	0.5250
NP*IPS	0.019205	0.022101	0.868955	0.3986
NP*RPS	-0.290882	0.312264	-0.931526	0.3663
OPP	-0.012254	0.006967	-1.758859	0.0990
OPP^2	0.000135	0.000222	0.609915	0.5510
OPP*IPS	-0.029792	0.011389	-2.616009	0.0195
OPP*RPS	0.057696	0.095940	0.601374	0.5566
IPS	0.249344	0.147972	1.685082	0.1127
IPS^2	0.091101	0.089343	1.019676	0.3240
IPS*RPS	1.446263	1.496627	0.966348	0.3492
RPS	3.682059	4.446425	0.828094	0.4206
RPS^2	-0.911275	1.118020	-0.815080	0.4278

R-squared	0.745447	Mean dependent var	0.000945
Adjusted R-squared	0.168460	S.D. dependent var	0.002472
S.E. of regression	0.002254	Akaike info criterion	-9.156400
Sum squared resid	7.62E-05	Schwarz criterion	-7.817983
Log likelihood	263.9100	Hannan-Quinn criter.	-8.646723
F-statistic	1.291964	Durbin-Watson stat	1.777291
Prob(F-statistic)	0.304682		

Table F4 Eviews' estimation for Residual test/ White heteroskedasticity test not including White cross term of explanatory variables of TEVRSi scores (detection of the problems of heteroscedasticity)

Heteroskedasticity Test: White

F-statistic	1.620296	Prob. F(7,42)	0.1563
Obs*R-squared	10.63145	Prob. Chi-Square(7)	0.1555
Scaled explained SS	25.14105	Prob. Chi-Square(7)	0.0007

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample: 1 50
Included observations: 50

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002731	0.002179	-1.253297	0.2170
BP^2	8.55E-05	3.96E-05	2.156674	0.0368
P^2	1.52E-07	9.34E-08	1.626289	0.1114
P2^2	-1.65E-12	1.09E-12	-1.513766	0.1376
NP^2	-8.94E-05	4.28E-05	-2.091036	0.0426
OPP^2	3.10E-05	1.48E-05	2.094392	0.0423
IPS^2	-0.016402	0.009808	-1.672284	0.1019

RPS^2	-0.063424	0.074956	-0.846155	0.4023

R-squared	0.212629	Mean dependent var	0.000945
Adjusted R-squared	0.081400	S.D. dependent var	0.002472
S.E. of regression	0.002369	Akaike info criterion	-9.107210
Sum squared resid	0.000236	Schwarz criterion	-8.801286
Log likelihood	235.6802	Hannan-Quinn criter.	-8.990712
F-statistic	1.620296	Durbin-Watson stat	2.404307
Prob(F-statistic)	0.156268		

Table F5 Eviews' estimation for Residual test/ White heteroskedasticity test including White cross term of explanatory variables of SEi scores (detection of the problems of heteroscedasticity)

Heteroskedasticity Test: White

F-statistic	1.183568	Prob. F(18,31)	0.3307
Obs*R-squared	20.36568	Prob. Chi-Square(18)	0.3126
Scaled explained SS	21.88054	Prob. Chi-Square(18)	0.2373

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample: 1 50
Included observations: 50
Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.003748	0.013422	-0.279260	0.7819
OP	5.35E-06	3.11E-06	1.719249	0.0955
OP^2	-3.30E-10	2.92E-10	-1.130381	0.2670
OP*IDRGP	-3.19E-09	3.66E-09	-0.871400	0.3902
OP*MPS	-6.92E-06	4.14E-06	-1.672118	0.1046
OP*UJ	-2.03E-06	5.63E-06	-0.360590	0.7209
OP*HAJ	-2.22E-07	8.34E-07	-0.266612	0.7915
IDRGP	-2.10E-05	3.24E-05	-0.648277	0.5216
IDRGP^2	2.35E-08	2.24E-08	1.048884	0.3023
IDRGP*MPS	2.04E-05	4.29E-05	0.474141	0.6387
IDRGP*UJ	1.64E-05	1.71E-05	0.960055	0.3445
IDRGP*HAJ	-3.90E-06	6.84E-06	-0.570434	0.5725
MPS	0.007960	0.029361	0.271116	0.7881
MPS^2	0.031668	0.027452	1.153591	0.2575
MPS*UJ	-0.004244	0.013683	-0.310178	0.7585
MPS*HAJ	-0.004700	0.007964	-0.590194	0.5593
UJ	-0.002252	0.016540	-0.136178	0.8926
UJ*HAJ	0.000864	0.004300	0.200936	0.8421
HAJ	0.003475	0.005091	0.682438	0.5000

R-squared	0.407314	Mean dependent var	0.001138
Adjusted R-squared	0.063173	S.D. dependent var	0.001915
S.E. of regression	0.001853	Akaike info criterion	-9.461547
Sum squared resid	0.000106	Schwarz criterion	-8.734978
Log likelihood	255.5387	Hannan-Quinn criter.	-9.184865
F-statistic	1.183568	Durbin-Watson stat	1.972622
Prob(F-statistic)	0.330702		

Table F6 Eviews' estimation for Residual test/ White heteroskedasticity test not including White cross term of explanatory variables of SEi scores (detection of the problems of heteroscedasticity)

Heteroskedasticity Test: White

F-statistic	1.920959	Prob. F(5,44)	0.1101
Obs*R-squared	8.958894	Prob. Chi-Square(5)	0.1107
Scaled explained SS	9.625282	Prob. Chi-Square(5)	0.0866

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample: 1 50
Included observations: 50

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002297	0.001091	2.105474	0.0410
OP^2	3.62E-11	3.43E-11	1.053898	0.2977
IDRGP^2	-5.43E-09	2.29E-09	-2.373956	0.0220
MPS^2	-0.003760	0.005113	-0.735215	0.4661
UJ^2	-0.001374	0.000883	-1.555747	0.1269
HAJ^2	-5.99E-05	0.000610	-0.098114	0.9223

R-squared	0.179178	Mean dependent var	0.001138
Adjusted R-squared	0.085903	S.D. dependent var	0.001915
S.E. of regression	0.001831	Akaike info criterion	-9.655906
Sum squared resid	0.000147	Schwarz criterion	-9.426463
Log likelihood	247.3976	Hannan-Quinn criter.	-9.568533
F-statistic	1.920959	Durbin-Watson stat	2.313341
Prob(F-statistic)	0.110055		

Table F7 Eviews' estimation for Residual test/ White heteroskedasticity test including White cross term of explanatory variables of TEVRSo scores (detection of the problems of heteroscedasticity)

Heteroskedasticity Test: White

F-statistic	0.824504	Prob. F(34,15)	0.6906
Obs*R-squared	32.57157	Prob. Chi-Square(34)	0.5376
Scaled explained SS	40.54486	Prob. Chi-Square(34)	0.2040

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample: 1 50
Included observations: 50
Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.165244	0.198168	-0.833860	0.4174
BP	0.015734	0.021310	0.738346	0.4717
BP^2	-0.000499	0.002558	-0.195079	0.8479
BP*P	-0.000130	0.000203	-0.637501	0.5334

BP*P2	4.14E-07	8.55E-07	0.484296	0.6352
BP*NP	-0.000224	0.004195	-0.053448	0.9581
BP*OPP	0.000323	0.000917	0.351949	0.7298
BP*IPS	-0.010023	0.016198	-0.618813	0.5453
BP*RPS	0.012709	0.217563	0.058414	0.9542
P	0.002338	0.004042	0.578371	0.5716
P^2	-1.72E-05	3.49E-05	-0.492199	0.6297
P*P2	6.09E-08	1.35E-07	0.449783	0.6593
P*NP	-0.000171	0.000269	-0.637929	0.5331
P*OPP	0.000127	0.000119	1.064085	0.3041
P*IPS	-0.001238	0.001827	-0.677671	0.5083
P*RPS	-0.014773	0.040964	-0.360635	0.7234
P2^2	-8.48E-11	2.03E-10	-0.417817	0.6820
P2*NP	6.26E-07	1.05E-06	0.598348	0.5585
P2*OPP	-4.28E-07	5.60E-07	-0.765214	0.4560
P2*IPS	1.43E-06	6.69E-06	0.213156	0.8341
P2*RPS	3.26E-05	9.49E-05	0.343134	0.7363
NP	0.010550	0.025976	0.406136	0.6904
NP^2	-0.000436	0.001762	-0.247545	0.8078
NP*OPP	9.95E-05	0.000942	0.105675	0.9172
NP*IPS	0.030326	0.023553	1.287609	0.2174
NP*RPS	-0.262931	0.332777	-0.790112	0.4418
OPP	-0.004660	0.007425	-0.627708	0.5396
OPP^2	-9.69E-06	0.000236	-0.040979	0.9679
OPP*IPS	-0.028182	0.012137	-2.322031	0.0347
OPP*RPS	0.041464	0.102243	0.405549	0.6908
IPS	0.232015	0.157692	1.471317	0.1619
IPS^2	0.060214	0.095212	0.632423	0.5366
IPS*RPS	1.072227	1.594942	0.672267	0.5116
RPS	2.079931	4.738515	0.438941	0.6670
RPS^2	-0.842633	1.191463	-0.707225	0.4903

R-squared	0.651431	Mean dependent var	0.001186
Adjusted R-squared	-0.138657	S.D. dependent var	0.002251
S.E. of regression	0.002402	Akaike info criterion	-9.029153
Sum squared resid	8.65E-05	Schwarz criterion	-7.690737
Log likelihood	260.7288	Hannan-Quinn criter.	-8.519477
F-statistic	0.824504	Durbin-Watson stat	1.700464
Prob(F-statistic)	0.690620		

Table F8 Eviews' estimation for Residual test/ White heteroskedasticity test not including White cross term of explanatory variables of TEVRSo scores (detection of the problems of heteroscedasticity)

Heteroskedasticity Test: White

F-statistic	1.997920	Prob. F(7,42)	0.0782
Obs*R-squared	12.49025	Prob. Chi-Square(7)	0.0855
Scaled explained SS	15.54777	Prob. Chi-Square(7)	0.0296

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample: 1 50
Included observations: 50

Variable	Coefficient	Std. Error	t-Statistic	Prob.

C	-0.000774	0.001937	-0.399322	0.6917
BP^2	9.00E-05	3.52E-05	2.554475	0.0143
P^2	7.19E-08	8.30E-08	0.865873	0.3915
P2^2	-8.22E-13	9.70E-13	-0.847037	0.4018
NP^2	-8.36E-05	3.80E-05	-2.197424	0.0336
OPP^2	1.79E-05	1.32E-05	1.356994	0.1820
IPS^2	-0.015625	0.008719	-1.792044	0.0803
RPS^2	-0.057175	0.066631	-0.858087	0.3957

R-squared	0.249805	Mean dependent var	0.001186
Adjusted R-squared	0.124772	S.D. dependent var	0.002251
S.E. of regression	0.002106	Akaike info criterion	-9.342655
Sum squared resid	0.000186	Schwarz criterion	-9.036731
Log likelihood	241.5664	Hannan-Quinn criter.	-9.226157
F-statistic	1.997920	Durbin-Watson stat	2.388724
Prob(F-statistic)	0.078151		

Table F9 Eviews' estimation for Residual test/ White heteroskedasticity test including White cross term of explanatory variables of SEo scores (detection of the problems of heteroscedasticity)

Heteroskedasticity Test: White

F-statistic	0.551832	Prob. F(18,31)	0.9070
Obs*R-squared	12.13322	Prob. Chi-Square(18)	0.8403
Scaled explained SS	18.04400	Prob. Chi-Square(18)	0.4528

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample: 1 50
Included observations: 50
Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002958	0.010057	-0.294127	0.7706
OP	1.95E-06	2.33E-06	0.836076	0.4095
OP^2	-5.85E-11	2.19E-10	-0.267077	0.7912
OP*IDRGP	-1.65E-09	2.74E-09	-0.602128	0.5515
OP*MPS	-3.56E-06	3.10E-06	-1.147189	0.2601
OP*UJ	-2.30E-07	4.22E-06	-0.054529	0.9569
OP*HAJ	-1.05E-07	6.25E-07	-0.168279	0.8675
IDRGP	-1.11E-06	2.43E-05	-0.045803	0.9638
IDRGP^2	3.74E-09	1.68E-08	0.222580	0.8253
IDRGP*MPS	-3.28E-06	3.22E-05	-0.101824	0.9196
IDRGP*UJ	4.69E-06	1.28E-05	0.365368	0.7173
IDRGP*HAJ	-7.56E-07	5.12E-06	-0.147483	0.8837
MPS	0.012583	0.021999	0.572004	0.5714
MPS^2	0.008268	0.020568	0.401990	0.6904
MPS*UJ	-0.004188	0.010252	-0.408526	0.6857
MPS*HAJ	-0.000876	0.005967	-0.146780	0.8843
UJ	-0.001429	0.012392	-0.115314	0.9089
UJ*HAJ	0.000423	0.003222	0.131231	0.8964
HAJ	0.000532	0.003815	0.139572	0.8899

R-squared	0.242664	Mean dependent var	0.000641
Adjusted R-squared	-0.197079	S.D. dependent var	0.001269
S.E. of regression	0.001389	Akaike info criterion	-10.03892
Sum squared resid	5.98E-05	Schwarz criterion	-9.312355
Log likelihood	269.9731	Hannan-Quinn criter.	-9.762243
F-statistic	0.551832	Durbin-Watson stat	1.736401
Prob(F-statistic)	0.906952		

Table F10 Eviews' estimation for Residual test/ White heteroskedasticity test not including White cross term of explanatory variables of SEo scores (detection of the problems of heteroscedasticity)

Heteroskedasticity Test: White

F-statistic	1.638260	Prob. F(5,44)	0.1699
Obs*R-squared	7.847383	Prob. Chi-Square(5)	0.1648
Scaled explained SS	11.67029	Prob. Chi-Square(5)	0.0396

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample: 1 50
Included observations: 50

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001229	0.000733	1.676981	0.1006
OP^2	3.68E-11	2.30E-11	1.597756	0.1173
IDRGP^2	-3.13E-09	1.54E-09	-2.037338	0.0477
MPS^2	-0.001784	0.003435	-0.519448	0.6061
UI^2	-0.000569	0.000593	-0.959748	0.3424
HAI^2	-0.000401	0.000410	-0.977304	0.3338

R-squared	0.156948	Mean dependent var	0.000641
Adjusted R-squared	0.061146	S.D. dependent var	0.001269
S.E. of regression	0.001230	Akaike info criterion	-10.45170
Sum squared resid	6.66E-05	Schwarz criterion	-10.22226
Log likelihood	267.2925	Hannan-Quinn criter.	-10.36433
F-statistic	1.638260	Durbin-Watson stat	1.937986
Prob(F-statistic)	0.169902		

Appendix G Other methods of regression analyses

Table G1 Eviews' OLS estimation for TEVRS; input-orientated DEA, changing dependent variables in exponential form of TE scores

Dependent Variable: E_VRSI
Method: Least Squares
Sample: 1 50
Included observations: 50
E_VRSI=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS
+C(8)*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	3.209235	0.174980	18.34059	0.0000
C(2)	-0.069305	0.018799	-3.686572	0.0006
C(3)	-0.003695	0.001342	-2.752873	0.0087
C(4)	8.28E-06	3.70E-06	2.236455	0.0307
C(5)	0.046600	0.019858	2.346641	0.0237
C(6)	-0.020712	0.008803	-2.352950	0.0234
C(7)	0.464420	0.182255	2.548184	0.0146
C(8)	0.565394	0.414275	1.364778	0.1796

R-squared	0.385128	Mean dependent var	2.674642
Adjusted R-squared	0.282649	S.D. dependent var	0.099994
S.E. of regression	0.084691	Akaike info criterion	-1.953966
Sum squared resid	0.301248	Schwarz criterion	-1.648042
Log likelihood	56.84915	Hannan-Quinn criter.	-1.837468
F-statistic	3.758124	Durbin-Watson stat	1.911566
Prob(F-statistic)	0.003009		

Table G2 Eviews' OLS estimation for SE; input-orientated DEA, changing dependent variables in exponential form of TE scores

Dependent Variable: E_SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
E_SEI= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	2.451604	0.097718	25.08852	0.0000
C(2)	-1.12E-05	1.51E-05	-0.740216	0.4631
C(3)	0.000394	0.000130	3.026045	0.0041
C(4)	0.114552	0.112462	1.018589	0.3140
C(5)	0.096059	0.045348	2.118273	0.0398
C(6)	0.042968	0.030961	1.387792	0.1722

R-squared	0.232225	Mean dependent var	2.659625
Adjusted R-squared	0.144977	S.D. dependent var	0.100355
S.E. of regression	0.092796	Akaike info criterion	-1.804666
Sum squared resid	0.378886	Schwarz criterion	-1.575223
Log likelihood	51.11664	Hannan-Quinn criter.	-1.717293
F-statistic	2.661684	Durbin-Watson stat	2.033010
Prob(F-statistic)	0.034652		

Table G3 Eviews' OLS estimation for TEVRS; output-orientated DEA, changing dependent variables in exponential form of TE scores

Dependent Variable: E_VRSO
Method: Least Squares
Sample: 1 50
Included observations: 50
E_VRSO=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS
+C(8)*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	3.063118	0.197821	15.48432	0.0000
C(2)	-0.074727	0.021253	-3.516002	0.0011
C(3)	-0.002810	0.001517	-1.852016	0.0711
C(4)	6.32E-06	4.19E-06	1.509721	0.1386
C(5)	0.060670	0.022450	2.702412	0.0099
C(6)	-0.021286	0.009952	-2.138964	0.0383
C(7)	0.530077	0.206046	2.572622	0.0137
C(8)	0.682337	0.468352	1.456890	0.1526

R-squared	0.373338	Mean dependent var	2.660405
Adjusted R-squared	0.268895	S.D. dependent var	0.111978
S.E. of regression	0.095746	Akaike info criterion	-1.708587
Sum squared resid	0.385027	Schwarz criterion	-1.402664
Log likelihood	50.71469	Hannan-Quinn criter.	-1.592090
F-statistic	3.574545	Durbin-Watson stat	2.071555
Prob(F-statistic)	0.004188		

Table G4 Eviews' OLS estimation for SO; output-orientated DEA, changing dependent variables in exponential form of TE scores

Dependent Variable: E_SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
E_SEO= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	2.529648	0.074117	34.13057	0.0000
C(2)	-1.13E-05	1.14E-05	-0.992483	0.3264
C(3)	0.000288	9.88E-05	2.916353	0.0056
C(4)	0.086958	0.085299	1.019444	0.3136
C(5)	0.066507	0.034395	1.933615	0.0596
C(6)	0.038260	0.023483	1.629227	0.1104

R-squared	0.233269	Mean dependent var	2.673131
Adjusted R-squared	0.146141	S.D. dependent var	0.076169
S.E. of regression	0.070383	Akaike info criterion	-2.357557
Sum squared resid	0.217967	Schwarz criterion	-2.128114
Log likelihood	64.93891	Hannan-Quinn criter.	-2.270183
F-statistic	2.677298	Durbin-Watson stat	1.820278
Prob(F-statistic)	0.033818		

Table G5 Eviews' OLS estimation for TEVRS; input-orientated DEA, changing dependent variables in semi-log form (ln) of TE scores

Dependent Variable: LN_VRSI
Method: Least Squares
Sample: 1 50
Included observations: 50
LN_VRSI=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS
+C(8)*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.208866	0.075250	2.775616	0.0082
C(2)	-0.028831	0.008085	-3.566134	0.0009
C(3)	-0.001567	0.000577	-2.715661	0.0096
C(4)	3.50E-06	1.59E-06	2.200679	0.0333
C(5)	0.019374	0.008540	2.268619	0.0285
C(6)	-0.008903	0.003786	-2.351722	0.0235
C(7)	0.197142	0.078379	2.515235	0.0158
C(8)	0.239368	0.178160	1.343557	0.1863

R-squared	0.374621	Mean dependent var	-0.017920
Adjusted R-squared	0.270391	S.D. dependent var	0.042640
S.E. of regression	0.036422	Akaike info criterion	-3.641668
Sum squared resid	0.055714	Schwarz criterion	-3.335745
Log likelihood	99.04171	Hannan-Quinn criter.	-3.525171
F-statistic	3.594182	Durbin-Watson stat	1.921104
Prob(F-statistic)	0.004042		

Table G6 Eviews' OLS estimation for SE; input-orientated DEA, changing dependent variables in semi-log form (ln) of TE scores

Dependent Variable: LN_SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
LN_SEI= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.107425	0.040036	-2.683227	0.0102
C(2)	-4.61E-06	6.17E-06	-0.746855	0.4591
C(3)	0.000160	5.34E-05	2.998918	0.0044
C(4)	0.047382	0.046076	1.028340	0.3094
C(5)	0.038591	0.018579	2.077104	0.0437
C(6)	0.016965	0.012685	1.337433	0.1880

R-squared	0.227987	Mean dependent var	-0.023605
Adjusted R-squared	0.140258	S.D. dependent var	0.041003
S.E. of regression	0.038019	Akaike info criterion	-3.589287
Sum squared resid	0.063600	Schwarz criterion	-3.359844
Log likelihood	95.73216	Hannan-Quinn criter.	-3.501913
F-statistic	2.598770	Durbin-Watson stat	2.046927
Prob(F-statistic)	0.038229		

Table G7 Eviews' OLS estimation for TEVRS; output-orientated DEA, changing dependent variables in semi-log form (ln) of TE scores

Dependent Variable: LN_VRSO
Method: Least Squares
Sample: 1 50
Included observations: 50
LN_VRSO=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS
+C(8)*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.148137	0.083388	1.776468	0.0829
C(2)	-0.031362	0.008959	-3.500628	0.0011
C(3)	-0.001193	0.000640	-1.866058	0.0690
C(4)	2.67E-06	1.76E-06	1.511788	0.1381
C(5)	0.025155	0.009464	2.658089	0.0111
C(6)	-0.008928	0.004195	-2.128303	0.0392
C(7)	0.223817	0.086855	2.576895	0.0136
C(8)	0.285312	0.197427	1.445154	0.1558

R-squared	0.370036	Mean dependent var	-0.023748
Adjusted R-squared	0.265043	S.D. dependent var	0.047079
S.E. of regression	0.040360	Akaike info criterion	-3.436294
Sum squared resid	0.068416	Schwarz criterion	-3.130370
Log likelihood	93.90734	Hannan-Quinn criter.	-3.319796
F-statistic	3.524361	Durbin-Watson stat	2.079913
Prob(F-statistic)	0.004586		

Table G8 Eviews' OLS estimation for SE; output-orientated DEA, changing dependent variables in semi-log form (ln) of TE scores

Dependent Variable: LN_SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
LN_SEO= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.073858	0.029702	-2.486620	0.0168
C(2)	-4.62E-06	4.58E-06	-1.009559	0.3182
C(3)	0.000114	3.96E-05	2.874560	0.0062
C(4)	0.034573	0.034184	1.011385	0.3174
C(5)	0.025924	0.013784	1.880774	0.0666
C(6)	0.015180	0.009411	1.613033	0.1139

R-squared	0.228445	Mean dependent var	-0.017755
Adjusted R-squared	0.140768	S.D. dependent var	0.030429
S.E. of regression	0.028206	Akaike info criterion	-4.186402
Sum squared resid	0.035005	Schwarz criterion	-3.956960
Log likelihood	110.6601	Hannan-Quinn criter.	-4.099029
F-statistic	2.605537	Durbin-Watson stat	1.833749
Prob(F-statistic)	0.037827		

Table G9 Eviews' OLS estimation for TEVRS; input-orientated DEA, changing dependent variables in reciprocal form of TE scores

Dependent Variable: _1_VRSI
Method: Least Squares
Sample: 1 50
Included observations: 50
_1_VRSI=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS
+C(8)*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.774168	0.082084	9.431424	0.0000
C(2)	0.030812	0.008819	3.493881	0.0011
C(3)	0.001693	0.000630	2.688679	0.0102
C(4)	-3.78E-06	1.74E-06	-2.176102	0.0352
C(5)	-0.020713	0.009316	-2.223485	0.0316
C(6)	0.009686	0.004129	2.345721	0.0238
C(7)	-0.213078	0.085497	-2.492236	0.0167
C(8)	-0.258442	0.194338	-1.329856	0.1907

R-squared	0.367988	Mean dependent var	1.019028
Adjusted R-squared	0.262653	S.D. dependent var	0.046267
S.E. of regression	0.039729	Akaike info criterion	-3.467825
Sum squared resid	0.066292	Schwarz criterion	-3.161901
Log likelihood	94.69563	Hannan-Quinn criter.	-3.351328
F-statistic	3.493494	Durbin-Watson stat	1.928193
Prob(F-statistic)	0.004851		

Table G10 Eviews' OLS estimation for SE; input-orientated DEA, changing dependent variables in reciprocal form of TE scores

Dependent Variable: _1_SEI
Method: Least Squares
Sample: 1 50
Included observations: 50
_1_SEI= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.112648	0.042397	26.24360	0.0000
C(2)	4.90E-06	6.54E-06	0.750385	0.4570
C(3)	-0.000169	5.65E-05	-2.982662	0.0046
C(4)	-0.050417	0.048794	-1.033261	0.3071
C(5)	-0.040414	0.019675	-2.054065	0.0459
C(6)	-0.017586	0.013433	-1.309171	0.1973

R-squared	0.225576	Mean dependent var	1.024747
Adjusted R-squared	0.137573	S.D. dependent var	0.043354
S.E. of regression	0.040261	Akaike info criterion	-3.474688
Sum squared resid	0.071323	Schwarz criterion	-3.245245
Log likelihood	92.86720	Hannan-Quinn criter.	-3.387315
F-statistic	2.563277	Durbin-Watson stat	2.054110
Prob(F-statistic)	0.040409		

Table G11 Eviews' OLS estimation for TEVRS; output-orientated DEA, changing dependent variables in reciprocal form of TE scores

Dependent Variable: _1_VRSO
Method: Least Squares
Sample: 1 50
Included observations: 50
_1_VRSO=C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS
+C(8)*RPS

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.838997	0.089887	9.333963	0.0000
C(2)	0.033649	0.009657	3.484300	0.0012
C(3)	0.001290	0.000689	1.871096	0.0683
C(4)	-2.87E-06	1.90E-06	-1.511203	0.1382
C(5)	-0.026827	0.010201	-2.629788	0.0119
C(6)	0.009591	0.004522	2.120929	0.0399
C(7)	-0.241040	0.093624	-2.574558	0.0137
C(8)	-0.305815	0.212812	-1.437023	0.1581

R-squared	0.367423	Mean dependent var	1.025181
Adjusted R-squared	0.261993	S.D. dependent var	0.050642
S.E. of regression	0.043505	Akaike info criterion	-3.286213
Sum squared resid	0.079495	Schwarz criterion	-2.980289
Log likelihood	90.15532	Hannan-Quinn criter.	-3.169715
F-statistic	3.485006	Durbin-Watson stat	2.084903
Prob(F-statistic)	0.004926		

Table G12 Eviews' OLS estimation for SE; output-orientated DEA, changing dependent variables in reciprocal form of TE scores

Dependent Variable: _1_SEO
Method: Least Squares
Sample: 1 50
Included observations: 50
_1_SEO= C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.076260	0.031074	34.63546	0.0000
C(2)	4.88E-06	4.79E-06	1.018139	0.3142
C(3)	-0.000118	4.14E-05	-2.850508	0.0066
C(4)	-0.036016	0.035762	-1.007087	0.3194
C(5)	-0.026706	0.014420	-1.851938	0.0708
C(6)	-0.015781	0.009846	-1.602906	0.1161

R-squared	0.225721	Mean dependent var	1.018383
Adjusted R-squared	0.137735	S.D. dependent var	0.031778
S.E. of regression	0.029509	Akaike info criterion	-4.096102
Sum squared resid	0.038313	Schwarz criterion	-3.866659
Log likelihood	108.4026	Hannan-Quinn criter.	-4.008729
F-statistic	2.565412	Durbin-Watson stat	1.840753
Prob(F-statistic)	0.040274		

Table G13 Eviews' Tobit estimation for TEVRS (truncated sample); input-orientated DEA, changing dependent variables in reciprocal form of TE scores

Dependent Variable: _1_VRSI
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Sample: 1 50
Included observations: 50
Truncated sample
Left censoring (value) at zero
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives
INDEX = C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS
+C(8)*RPS

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.774168	0.075231	10.29054	0.0000
C(2)	0.030812	0.008083	3.812143	0.0001
C(3)	0.001693	0.000577	2.933594	0.0034
C(4)	-3.78E-06	1.59E-06	-2.374326	0.0176
C(5)	-0.020713	0.008538	-2.426025	0.0153
C(6)	0.009686	0.003785	2.559395	0.0105
C(7)	-0.213078	0.078359	-2.719257	0.0065
C(8)	-0.258442	0.178114	-1.450994	0.1468
Error Distribution				
SCALE:C(9)	0.036412	0.003641	10.00004	0.0000

Mean dependent var	1.019028	S.D. dependent var	0.046267
S.E. of regression	0.040211	Akaike info criterion	-3.427825
Sum squared resid	0.066292	Schwarz criterion	-3.083661
Log likelihood	94.69563	Hannan-Quinn criter.	-3.296765
Avg. log likelihood	1.893913		
Left censored obs	0	Right censored obs	0
Uncensored obs	50	Total obs	50

Table G14 Eviews' Tobit estimation for TEVRS (not truncated sample); input-orientated DEA, changing dependent variables in reciprocal form of TE scores

Dependent Variable: _1_VRSI
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Sample: 1 50
Included observations: 50
Left censoring (value) at zero
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives
INDEX = C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS
+C(8)*RPS

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.774168	0.075231	10.29054	0.0000
C(2)	0.030812	0.008083	3.812143	0.0001

C(3)	0.001693	0.000577	2.933594	0.0034
C(4)	-3.78E-06	1.59E-06	-2.374326	0.0176
C(5)	-0.020713	0.008538	-2.426025	0.0153
C(6)	0.009686	0.003785	2.559395	0.0105
C(7)	-0.213078	0.078359	-2.719257	0.0065
C(8)	-0.258442	0.178114	-1.450994	0.1468
		Error Distribution		
SCALE:C(9)	0.036412	0.003641	10.00004	0.0000

Mean dependent var	1.019028	S.D. dependent var	0.046267
S.E. of regression	0.040211	Akaike info criterion	-3.427825
Sum squared resid	0.066292	Schwarz criterion	-3.083661
Log likelihood	94.69563	Hannan-Quinn criter.	-3.296765
Avg. log likelihood	1.893913		
Left censored obs	0	Right censored obs	0
Uncensored obs	50	Total obs	50

Table G15 Eviews' Tobit estimation for SE (truncated sample); input-orientated DEA, changing dependent variables in reciprocal form of TE scores

Dependent Variable: _1_SEI
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Sample: 1 50
Included observations: 50
Truncated sample
Left censoring (value) at zero
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives
INDEX = C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	1.112648	0.039772	27.97578	0.0000
C(2)	4.90E-06	6.13E-06	0.799914	0.4238
C(3)	-0.000169	5.30E-05	-3.179529	0.0015
C(4)	-0.050417	0.045773	-1.101460	0.2707
C(5)	-0.040414	0.018457	-2.189641	0.0286
C(6)	-0.017586	0.012601	-1.395581	0.1628
		Error Distribution		
SCALE:C(7)	0.037768	0.003777	10.00001	0.0000

Mean dependent var	1.024747	S.D. dependent var	0.043354
S.E. of regression	0.040727	Akaike info criterion	-3.434688
Sum squared resid	0.071323	Schwarz criterion	-3.167005
Log likelihood	92.86720	Hannan-Quinn criter.	-3.332753
Avg. log likelihood	1.857344		
Left censored obs	0	Right censored obs	0
Uncensored obs	50	Total obs	50

Table G16 Eviews' Tobit estimation for SE (not truncated sample); input-orientated DEA, changing dependent variables in reciprocal form of TE scores

Dependent Variable: _1_SEI
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Sample: 1 50
Included observations: 50
Left censoring (value) at zero
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives
INDEX = C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	1.112648	0.039772	27.97578	0.0000
C(2)	4.90E-06	6.13E-06	0.799914	0.4238
C(3)	-0.000169	5.30E-05	-3.179529	0.0015
C(4)	-0.050417	0.045773	-1.101460	0.2707
C(5)	-0.040414	0.018457	-2.189641	0.0286
C(6)	-0.017586	0.012601	-1.395581	0.1628
		Error Distribution		
SCALE:C(7)	0.037768	0.003777	10.00001	0.0000

Mean dependent var	1.024747	S.D. dependent var	0.043354
S.E. of regression	0.040727	Akaike info criterion	-3.434688
Sum squared resid	0.071323	Schwarz criterion	-3.167005
Log likelihood	92.86720	Hannan-Quinn criter.	-3.332753
Avg. log likelihood	1.857344		
Left censored obs	0	Right censored obs	0
Uncensored obs	50	Total obs	50

Table G17 Eviews' Tobit estimation for TEVRS (truncated sample); output-orientated DEA, changing dependent variables in reciprocal form of TE scores

Dependent Variable: _1_VRSO
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Sample: 1 50
Included observations: 50
Truncated sample
Left censoring (value) at zero
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives
INDEX = C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS +C(8)*RPS

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.838997	0.082382	10.18420	0.0000
C(2)	0.033649	0.008851	3.801689	0.0001
C(3)	0.001290	0.000632	2.041536	0.0412
C(4)	-2.87E-06	1.74E-06	-1.648861	0.0992
C(5)	-0.026827	0.009349	-2.869338	0.0041

C(6)	0.009591	0.004144	2.314127	0.0207
C(7)	-0.241040	0.085807	-2.809078	0.0050
C(8)	-0.305815	0.195045	-1.567923	0.1169

Error Distribution

SCALE:C(9)	0.039873	0.003987	10.00004	0.0000

Mean dependent var	1.025181	S.D. dependent var	0.050642
S.E. of regression	0.044033	Akaike info criterion	-3.246213
Sum squared resid	0.079495	Schwarz criterion	-2.902049
Log likelihood	90.15532	Hannan-Quinn criter.	-3.115153
Avg. log likelihood	1.803106		

Left censored obs	0	Right censored obs	0
Uncensored obs	50	Total obs	50

Table G18 Eviews' Tobit estimation for TEVRS (not truncated sample); output-orientated DEA, changing dependent variables in reciprocal form of TE scores

Dependent Variable: _1_VRSO
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Sample: 1 50
Included observations: 50
Left censoring (value) at zero
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives
INDEX = C(1)+C(2)*BP+C(3)*P+C(4)*P2+C(5)*NP+C(6)*OPP+C(7)*IPS
+C(8)*RPS

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.838997	0.082382	10.18420	0.0000
C(2)	0.033649	0.008851	3.801689	0.0001
C(3)	0.001290	0.000632	2.041536	0.0412
C(4)	-2.87E-06	1.74E-06	-1.648861	0.0992
C(5)	-0.026827	0.009349	-2.869338	0.0041
C(6)	0.009591	0.004144	2.314127	0.0207
C(7)	-0.241040	0.085807	-2.809078	0.0050
C(8)	-0.305815	0.195045	-1.567923	0.1169

Error Distribution

SCALE:C(9)	0.039873	0.003987	10.00004	0.0000

Mean dependent var	1.025181	S.D. dependent var	0.050642
S.E. of regression	0.044033	Akaike info criterion	-3.246213
Sum squared resid	0.079495	Schwarz criterion	-2.902049
Log likelihood	90.15532	Hannan-Quinn criter.	-3.115153
Avg. log likelihood	1.803106		

Left censored obs	0	Right censored obs	0
Uncensored obs	50	Total obs	50

Table G19 Eviews' Tobit estimation for SE (truncated sample); output-orientated DEA, changing dependent variables in reciprocal form of TE scores

Dependent Variable: _1_SEO
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Sample: 1 50
Included observations: 50
Truncated sample
Left censoring (value) at zero
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives
INDEX = C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	1.076260	0.029150	36.92154	0.0000
C(2)	4.88E-06	4.49E-06	1.085340	0.2778
C(3)	-0.000118	3.89E-05	-3.038652	0.0024
C(4)	-0.036016	0.033548	-1.073558	0.2830
C(5)	-0.026706	0.013528	-1.974174	0.0484
C(6)	-0.015781	0.009236	-1.708704	0.0875
Error Distribution				
SCALE:C(7)	0.027682	0.002768	10.00001	0.0000

Mean dependent var	1.018383	S.D. dependent var	0.031778
S.E. of regression	0.029850	Akaike info criterion	-4.056102
Sum squared resid	0.038313	Schwarz criterion	-3.788419
Log likelihood	108.4026	Hannan-Quinn criter.	-3.954167
Avg. log likelihood	2.168051		
Left censored obs	0	Right censored obs	0
Uncensored obs	50	Total obs	50

Table G20 Eviews' Tobit estimation for SE (not truncated sample); output-orientated DEA, changing dependent variables in reciprocal form of TE scores

Dependent Variable: _1_SEO
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Sample: 1 50
Included observations: 50
Left censoring (value) at zero
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives
INDEX = C(1)+C(2)*OP+C(3)*IDRGP+C(4)*MPS+C(5)*UJ+C(6)*HAJ

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	1.076260	0.029150	36.92154	0.0000
C(2)	4.88E-06	4.49E-06	1.085340	0.2778
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C(4)	-0.036016	0.033548	-1.073558	0.2830
C(5)	-0.026706	0.013528	-1.974174	0.0484
C(6)	-0.015781	0.009236	-1.708704	0.0875
Error Distribution				
SCALE:C(7)	0.027682	0.002768	10.00001	0.0000

Mean dependent var	1.018383	S.D. dependent var	0.031778
S.E. of regression	0.029850	Akaike info criterion	-4.056102
Sum squared resid	0.038313	Schwarz criterion	-3.788419
Log likelihood	108.4026	Hannan-Quinn criter.	-3.954167
Avg. log likelihood	2.168051		

Left censored obs	0	Right censored obs	0
Uncensored obs	50	Total obs	50

Appendix H Relation of explanatory variables

Health care service

- **Out-patient service**

Figure H1 Relation between out-patient visits per physician and graduated medical student per physician staff

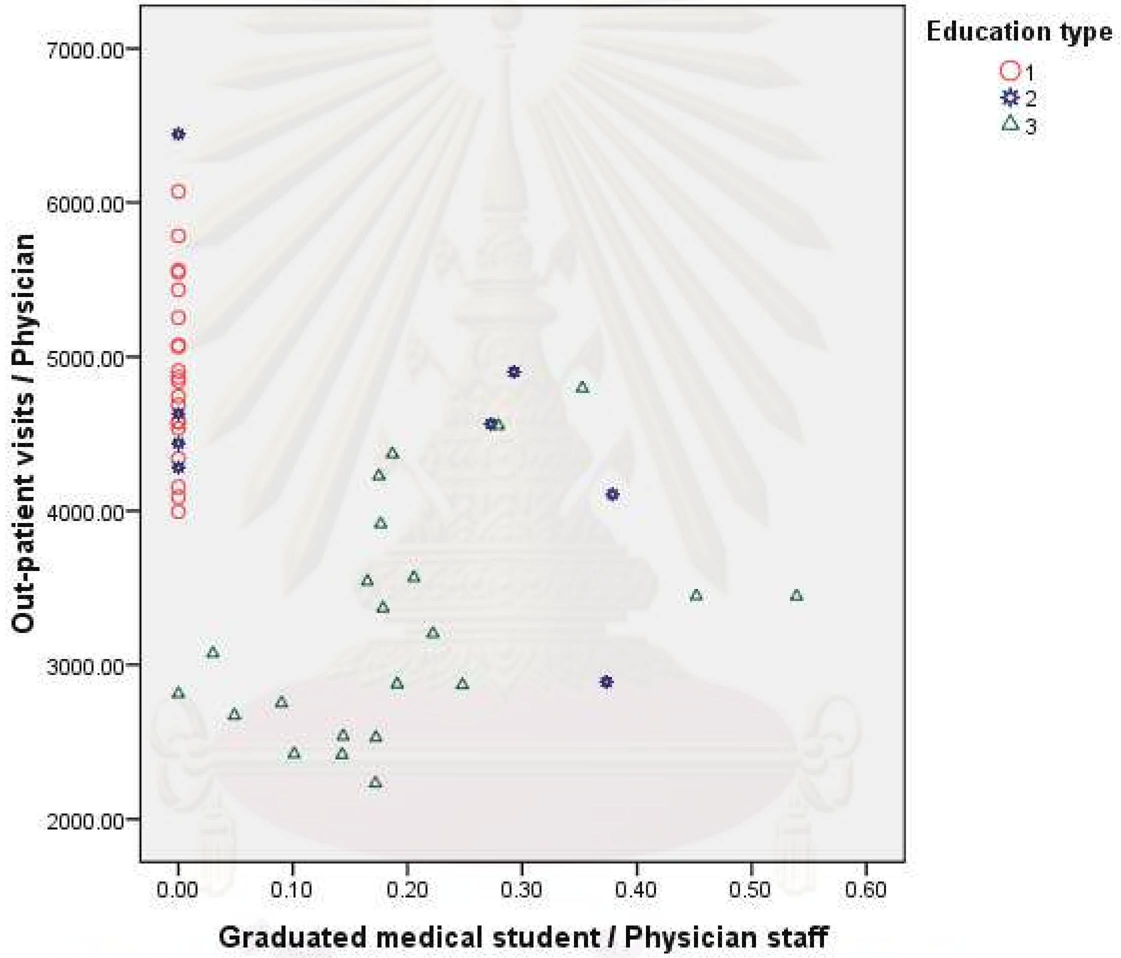
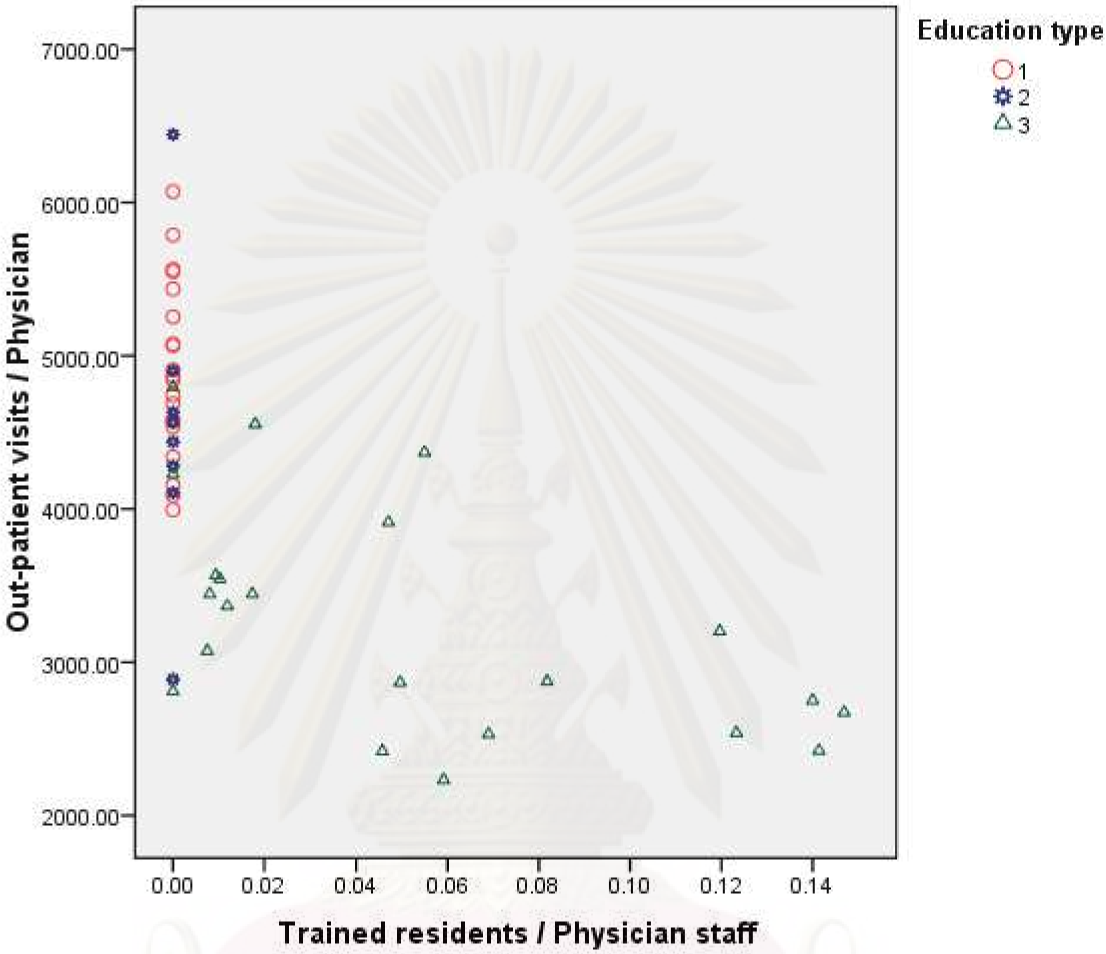


Figure H2 Relation between out-patient visits per physician and trained residents per physician staff



- **In-patient service**

Figure H3 Relation between in-patient visits*DRG per physician and graduated medical student per physician staff

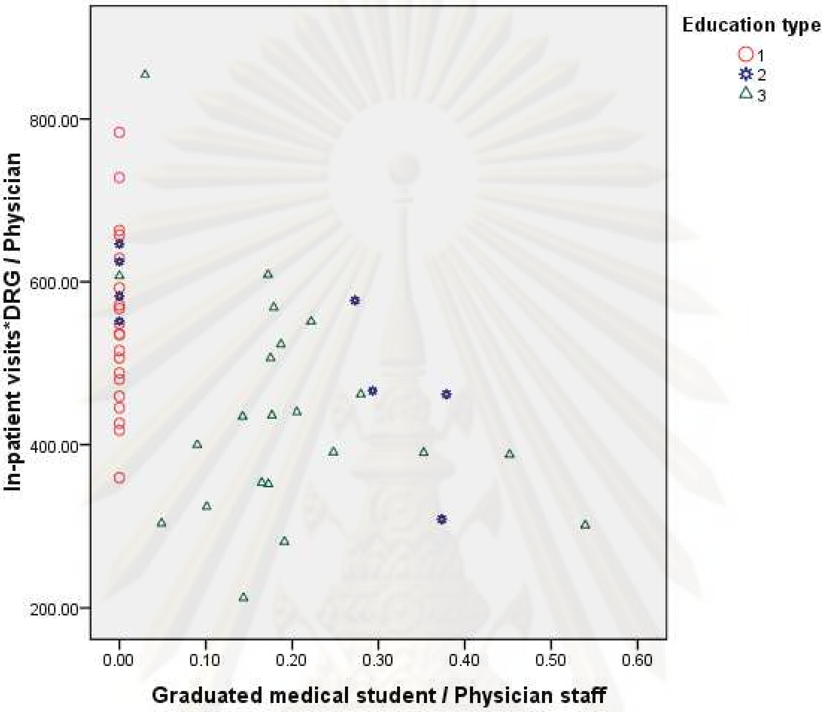


Figure H4 Relation between in-patient visits*DRG per physician and trained interns per physician staff

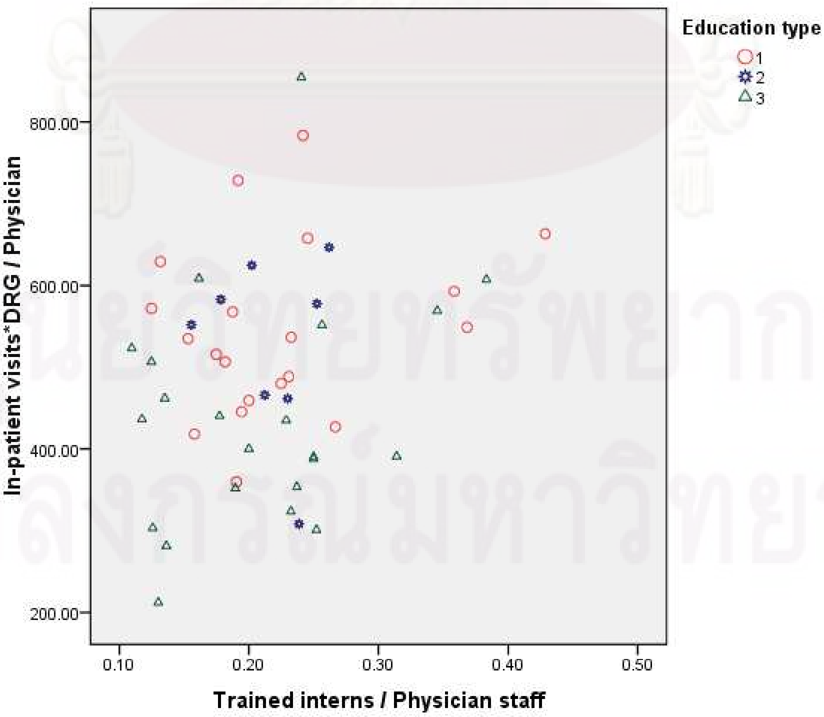
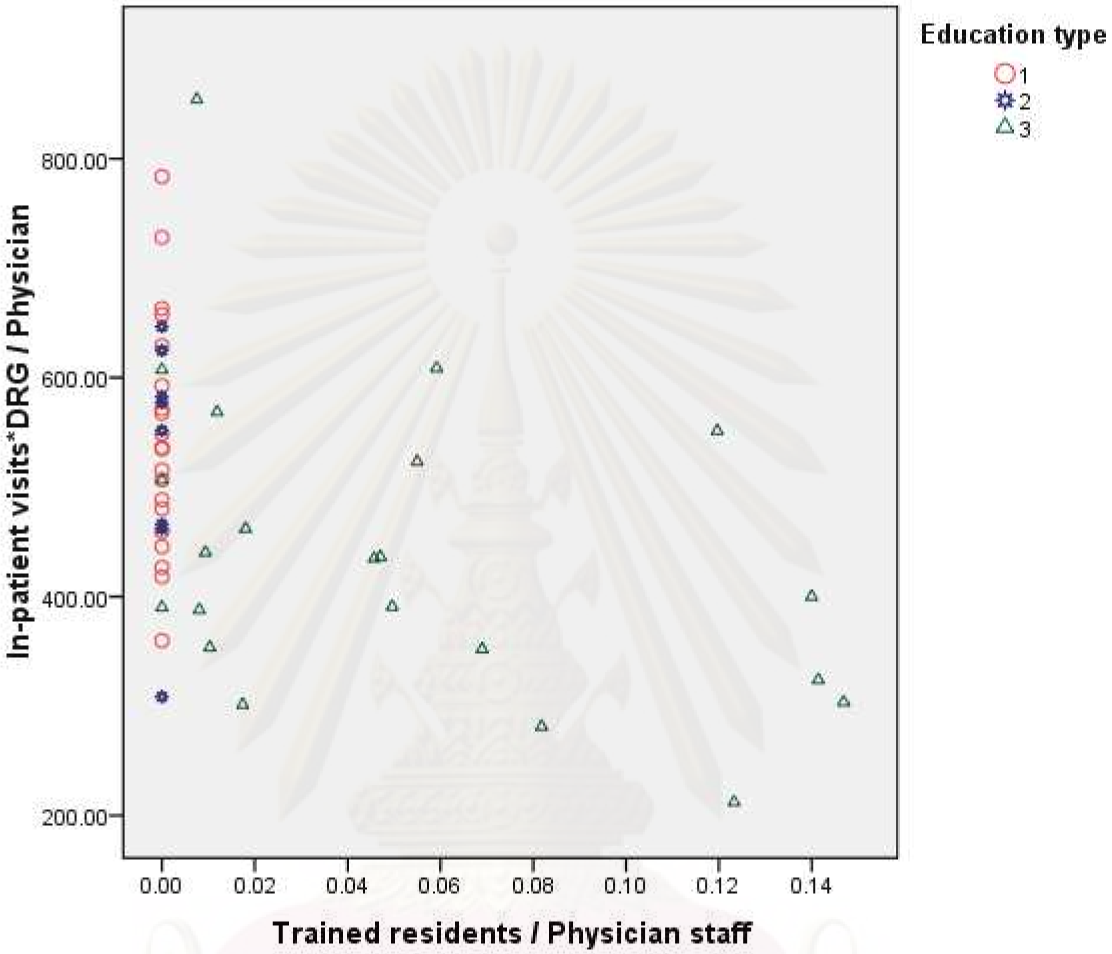


Figure H5 Relation between in-patient visits*DRG per physician and trained residents per physician staff



- **Medical student teaching**

Figure H6 Relation between graduated medical student per physician staff and beds per physician

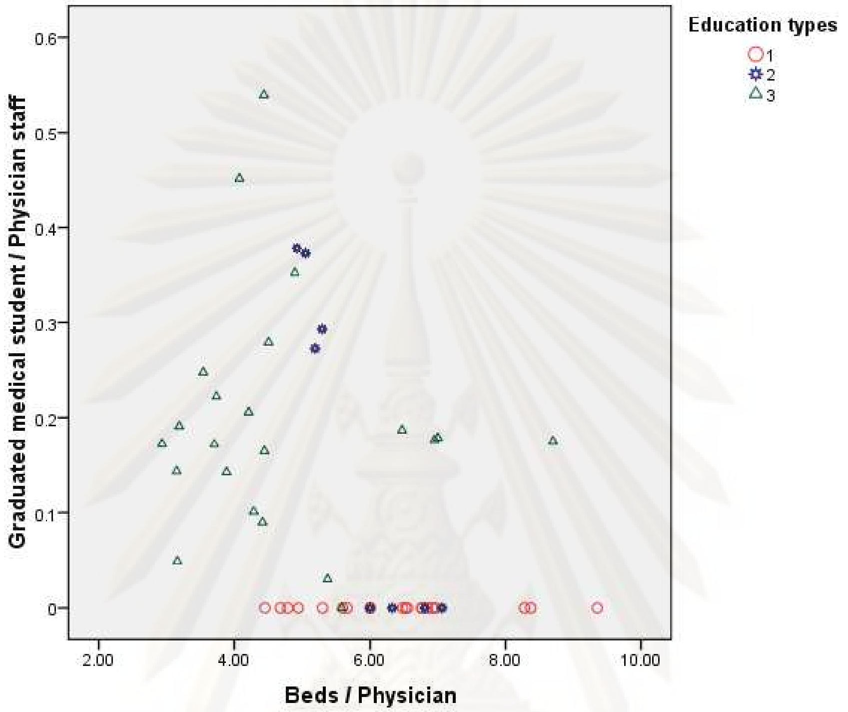


Figure H7 Relation between graduated medical student per physician staff and nurses per physician

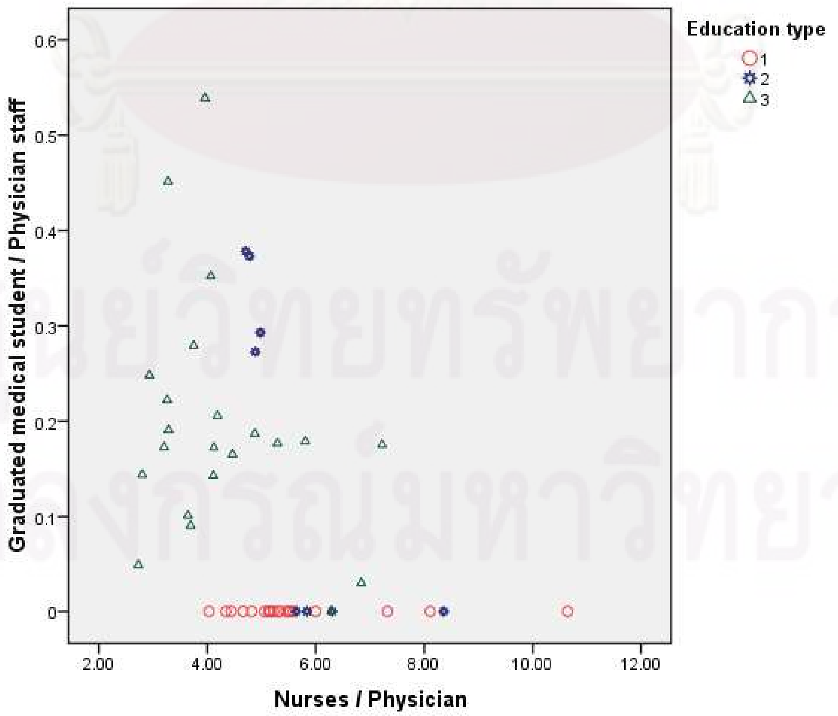


Figure H8 Relation between graduated medical student per physician staff and trained interns per physician staff

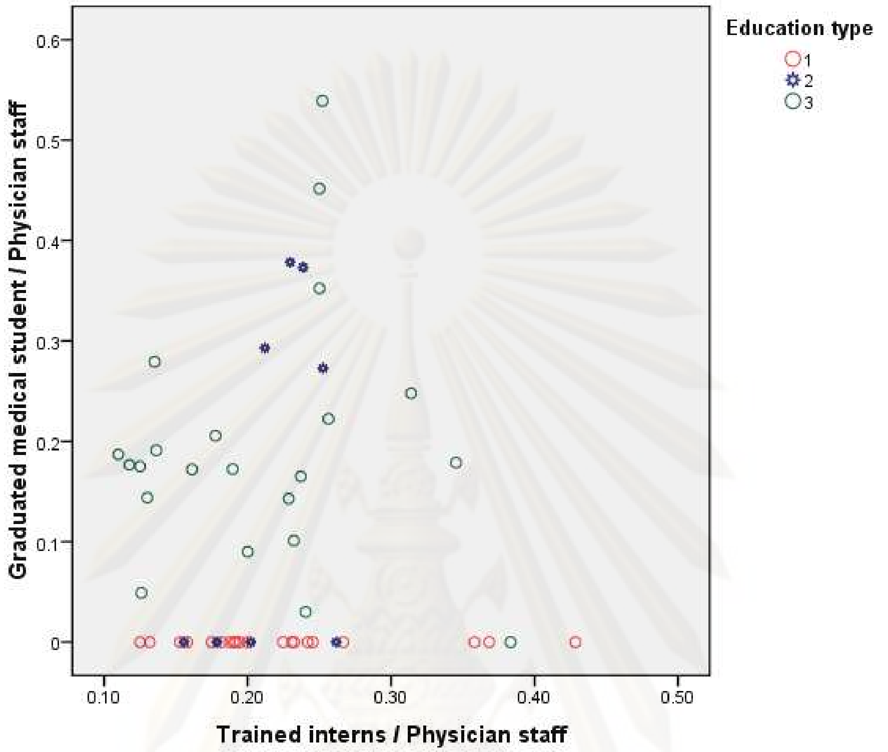
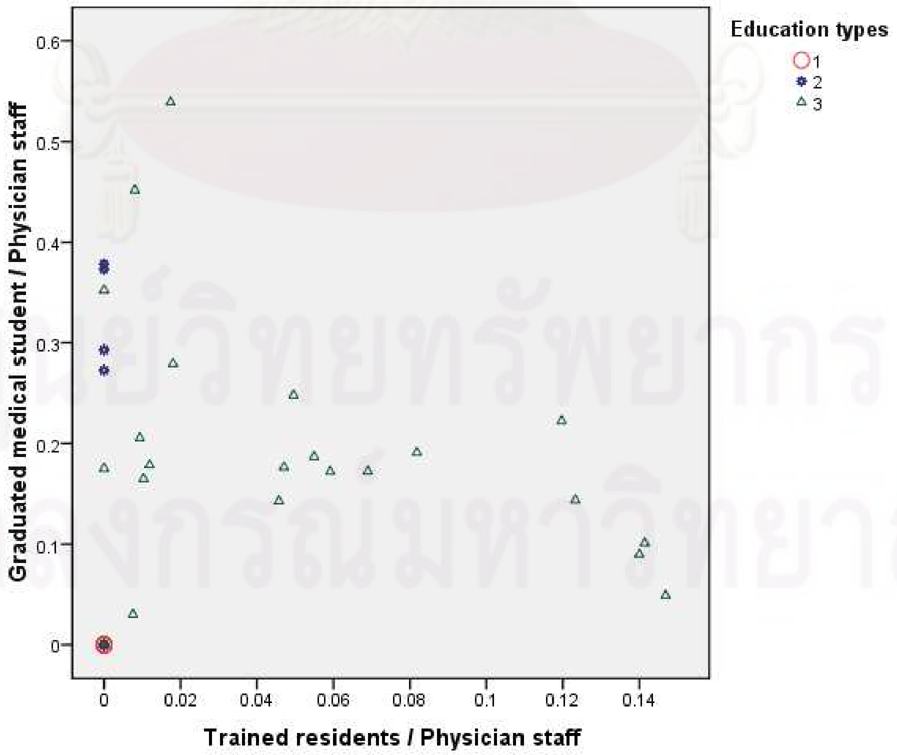


Figure H9 Relation between graduated medical student per physician staff and trained residents per physician staff



- **Intern training**

Figure H10 Relation between trained interns per physician staff and beds per physician

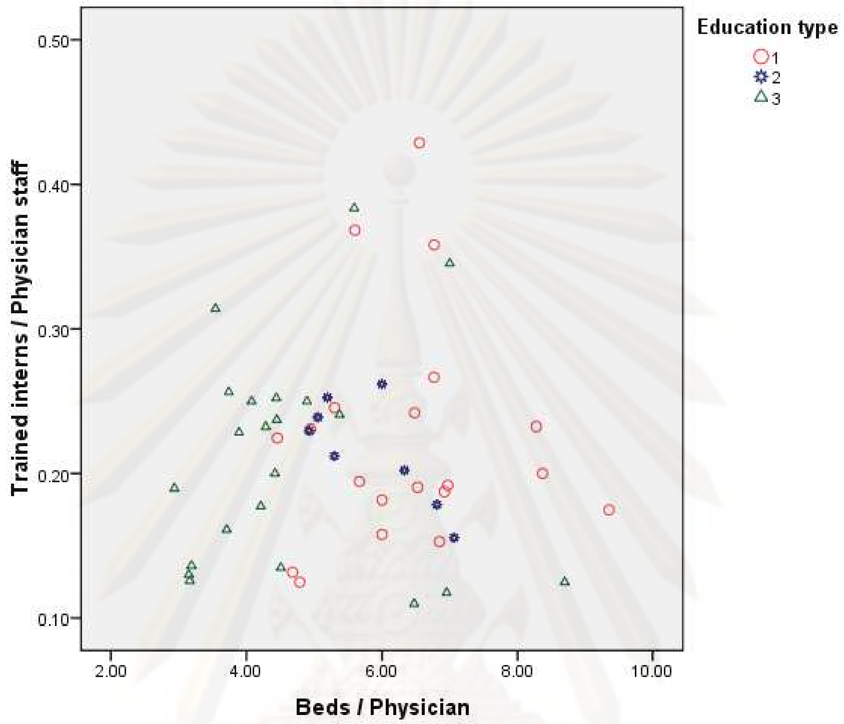
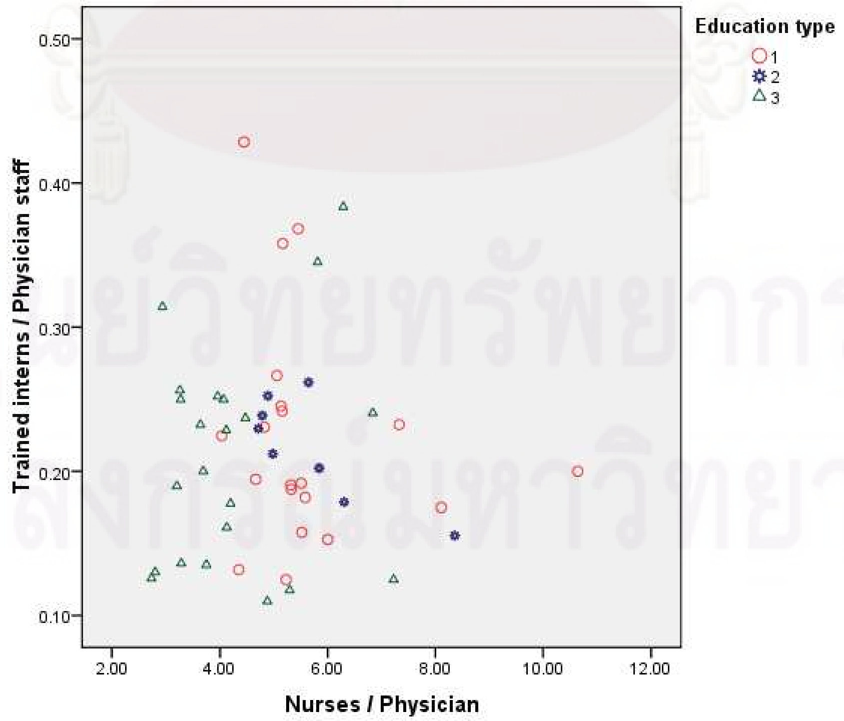


Figure H11 Relation between trained interns per physician staff and nurses per physician



- **Resident training**

Figure H12 Relation between trained residents per physician staff and beds per physician

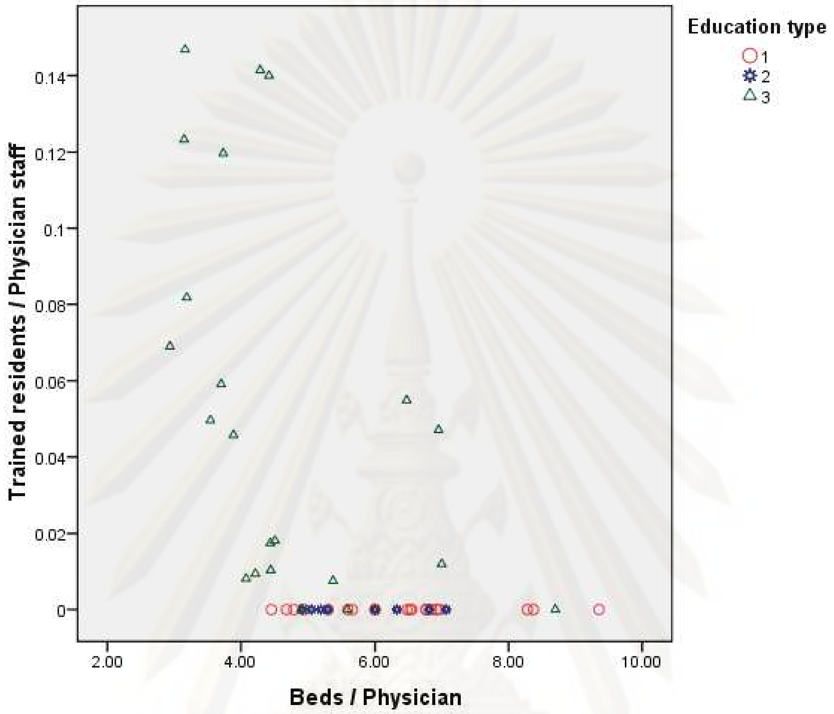


Figure H13 Relation between trained residents per physician staff and nurses per physician

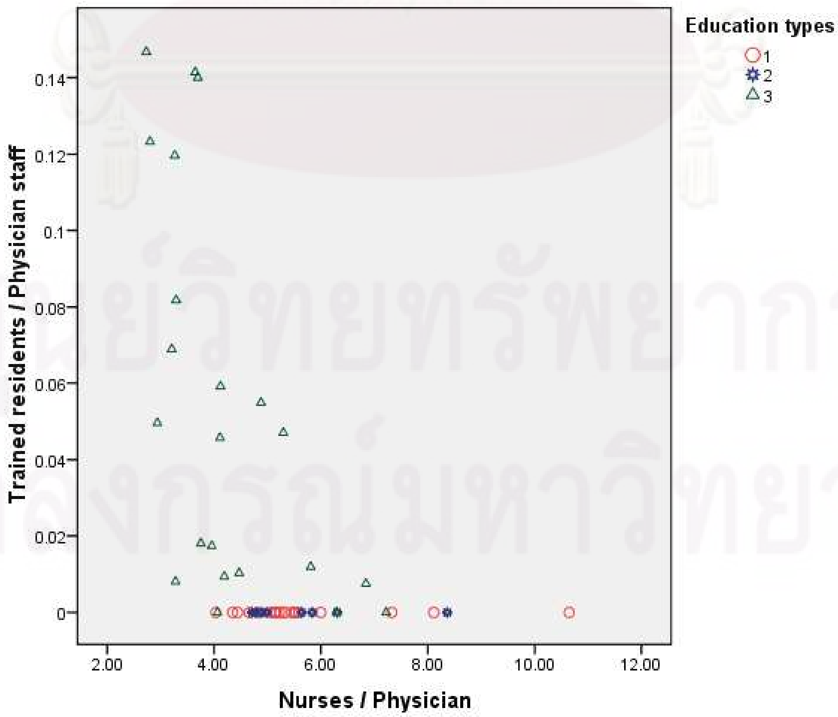
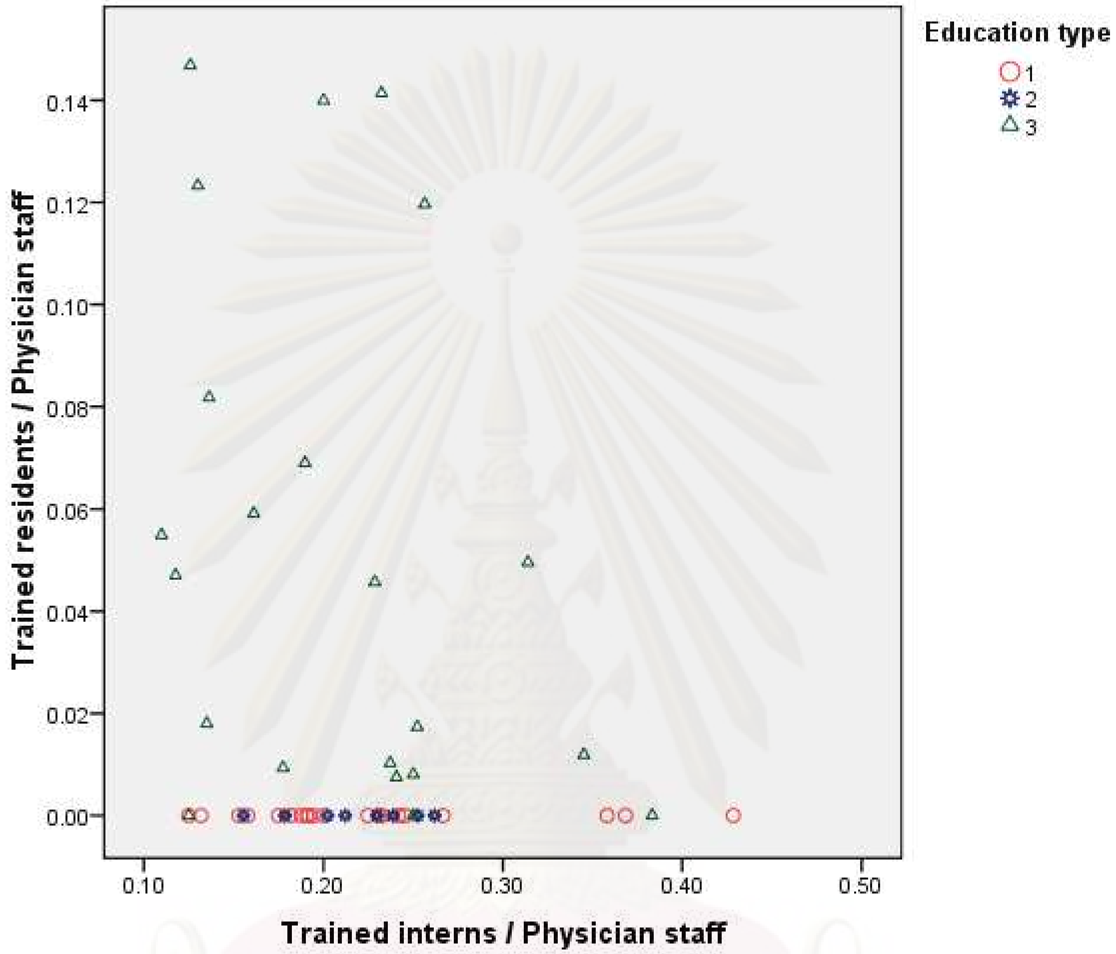


Figure H14 Relation between trained residents per physician staff and trained interns per physician staff



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