UNIVERSITAS INDONESIA

THE APPLICATION OF DATA ENVELOPMENT ANALYSIS IN MEASURING THE RELATIVE DISTRIBUTION CHANNEL PRODUCTIVITY OF INDONESIAN INFOCOM COMPANY

SKRIPSI

Diajukan sebagai salah satu syarat untuk memperoleh gelar Sarjana Ekonomi

SITI SULMA MARDIAH ZAHEDY
0604002415

FAKULTAS EKONOMI
PROGRAM STUDI MANAJEMEN

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ABSTRACT

This research aims to apply the quantitative tool *data envelopment analysis* (DEA) to help a local infocom (information & telecommunication) company in measuring and comparing the productivity (i.e. efficiency) of its internet service supply forces. The company chose its outsource agencies to be evaluated on their distribution channel productivity.

The DEA is able to point out which agency is the most productive (i.e. efficient) in its marketing effort relative to its peers. This unit afterward will be set as a role model to set goals for improvement for its less efficient peers.

For that reason, the management has chosen several factors to compute the relative marketing efficiencies (i.e. productivity):
(1) Number of employees (number of pesons)
(2) Marketing fee (monthly values in Rp.)
(3) Additional sales (number of subscribers)
(4) Revenue (monthly values in Rp.)

This research is able to compare the agencies to determine which is the most productive, and the least productive in their contribution to add subscribers and generate revenue. Also, the benchmarking outcome is used to suggest specific targets for improvement for the inefficient units.

<u>Keywords</u>: benchmarking; internal; marketing; productivity; efficiency; DEA; data envelopment analysis; internet service provider

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CHAPTER 1

INTRODUCTION

1.1 Background

Marketers are interested in knowing the productivity (i.e. ratio of the outputs produced to the inputs used) of their relevant 'production' units, be it retail stores or individual sales people (Donthu and Yoo, 1998; Boles et al., 1995 in Donthu et. al, 2005). The need for measuring marketing impact is intensified as firms feel increasing pressure to justify their marketing expenditures (Gupta and Zeithaml 2005; Rust et al., 2004; Srivastha et al., 1998, in Angulo, 2006).

Charnes et al. (1985, in Boles & Donthu, 1995) first discussed the potential application of *data envelopment analysis* (DEA) to gain insights of marketing efforts (1985, in Donthu et al., 2005). It was since then that researchers attempted at making DEA as a mainstream tool for marketing practice (Donthu, 2005). Among them are Donthu et al. (2005).

Donthu et al. (2005) suggested that DEA is useful in identifying the best performing units to be benchmarked against, as well as providing actionable measures for improvement of the company's marketing performance (Donthu et al., 2005, pp. 1474). They employed the application of data envelopment analysis (DEA) to measure *marketing productivity* (i.e. marketing efficiency). The DEA will help to map the company's units (e.g. outlets, branches) of which who is the most productive, the least productive, and the rest in between, in their marketing productivity. In addition, the most productive unit is set as a role model to set specific goals for improvement for its peers (i.e. the less efficient units).

There was an Indonesian infocom[1] company who wanted to evaluate the marketing productivity of their outsource supply force agencies. The company provides internet service for home users. The agencies build up to 60% of their total supply force for the service. Therefore, the management found it critical to know how well each of the the third party supply forces have performed in generating sales, given the resources allocated to them (i.e. how productive, or efficient, they were).

Seeing the usefulness of DEA in measuring the relative productivity, it would be beneficial for the company if one could put it into practice as a management tool to answer the management's query.

1.2 Research Objectives

The research attempts to analyze the productivity of an Indonesian infocom company internet service outsource supply force, the agencies, in South Jakarta by conducting *internal benchmarking*. Through the analysis, it was pointed out which agency is the most efficient in its effort relative to the rest. This outlet is then set as the benchmarking target (role model) for the other outlets (peer group) (Donthu et al., 2005). In addition, targets for improvements were set for the less efficient agencies.

1.3 Benefits of Research

a. For the company, the outcome of the research will definitely serve as a reliable source of information to assist the management in formulating future strategies.
b. For future marketing students, this thesis will serve as a reference and hopefully a source of ideas and inspirations to help with their academic needs and studies.

---

[1] Infocom is an abbreviation for information & telecommunication company.

1.4 Scope of Research

It needs to be emphasized that the research focuses solely in conducting an *internal benchmarking analysis* to benchmark the company's outsource agencies with the aid of a rigorous quantitative approach of data envelopment analysis (DEA) as suggested by Donthu et. al (2005)[2]. The agency units taken as the objects are those within the company's South Jakarta domain.

As per the management's request, the period of the analysis is within July to October of 2009. The analysis was conducted in a cross-sectional monthly manner, which was most appropriate with the fairly short term characteristics of the available data.

1.5 Outline

The paper is organized in the following way:

Chapter 1 INTRODUCTION

The first section of this paper covers the background of the study, the purpose of the research, scope of the research, brief explanation of the methodology to carry out the study, and the outline of the paper.

Chapter 2 LITERATURE REVIEW

Reviews of relevant concepts from and development of published literatures in benchmarking, marketing productivity, and data envelopment analysis are covered within this section.

Chapter 3 METHODOLOGY

This section covers comprehensively the methodology adopted in conducting the study. Explanation of the analysis tool used, data envelopment analysis (DEA), is covered within this section.

[2] They suggested that DEA is useful in identifying the best performing units to be benchmarked against, as well as providing actionable measures for improvement of the company's marketing performance (Donthu et al., 2005, pp. 1474).

Chapter 5 ANALYSES, RESULTS, AND DISCUSSIONS

The discussion section comprises of the following major subsections: the efficiency scores; improvement targets; agencis comparisons: between and within.

Chapter 6 CONCLUSION AND RECOMMENDATION

This section presents the conclusions of the study, as well as the managerial implications & suggestions for the company management, suggestions for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Benchmarking as a business improvement tool

An opening statement made by the American Productivity and Quality Center (APQC) in Robert Camp's book (1995) is that "the organizations that prosper and thrive will be those organizations that have learned to change—change quickly, change effectively, and change for the better" (Camp, 1995, pp. xiii). They further stated that the most efficient way for organizations to create efficient change is by *learning from the positive experience* of others.

There are an abundant of tools practiced by organizations around the globe in striving for organizational improvement (Global Benchmarking Network, 2008). Most of them are already widely known, such as TQM (Total Quality Management), BPR (Business Process Reengineering), QFD (Quality Function Deployment), Best Practice Benchmarking, etc. That practice of searching for best practice from others with superior performance, which will be then adopted or adapted to be implemented in order to raise the performance of an organization is known as the *best practice benchmarking* (Camp, 1995). That of which, is what the APQC meant by learning from the positive experience of others.

Robert Camp, often referred as the "father of benchmarking" (Nelson, 2009. Interview with Robert Camp), stated (1995, pp. 4) that "in a wide variety of firms, benchmarking has proven to be the instrumental process in their turning unproductive operations into efficient, profitable ones". This statement is already supported by facts on benchmarking around the globe. There are many case studies that focus on the success gained through benchmarking by pioneer companies who have implemented it. Among those pioneers in the benchmarking movement were Motorola, IBM, AT&T, and several others (Ammons, 1999). However, none of those pioneers wrote a more prominent role in benchmarking history than does the Xerox Corporation (Ammons, 1999; Mann, 2008).

Starting the benchmarking practice in the late 1970s, Xerox developed its own benchmarking approach to *not only* identify the gap of its performance, but also addressing the question of *why there are others that perform better* (Mann, 2008). Most among the benchmarking practices they conducted took organizations of different industries to learn their practices, which often resulted in identifying breakthrough practices (Camp, 1995; Mann, 2008). This resulted in Xerox becoming the recognized world-class industry leader, driving them to win the United States Malcolm Baldridge National Quality Award in 1989. In which the same year, Camp—who had been responsible for Xerox's benchmarking practice in all units—wrote his first book in benchmarking *Benchmarking: The Search for Industry Best Practices That Lead to Superior Performance* (Camp, 1995; Mann, 2008). This was the point where systematical approach to benchmarking practice introduced for the first time.

Ever since then, organizations around the globe began to acknowledge benchmarking practice as a critical quality tool (Camp, 1995). More so after the Malcolm Baldridge National Quality Award began including the need for benchmarking as a stated requirement for the application criteria (Camp, 1995).

How popular is benchmarking? A global survey conducted by Global Benchmarking Network (2008) reported that out of 454 companies from 44 countries surveyed, an average of 52% of the companies have used benchmarking as a business improvement tool. An earlier 2001 global survey on 32 countries by Jarra and Zairi showed that benchmarking was capable of producing significant benefits for the companies practicing it (Liang, 2005).

These facts show that benchmarking has been widely accepted as a tool that is proven to improve organization performance to a desired level by learning from others who owns better, superior practices (Mann, 2008).

2.2 Types of benchmarking

Benchmarking experts classified benchmarking into many types. Nevertheless, research studies have suggested several commonly accepted approaches to (i.e. types) of best practice benchmarking (Adebanjo et al.; Camp, 1995; Asian Productivity Organization, 2005):

Table 2.1 Types of benchmarking

Type	Description
Internal	This type of benchmarking compares among *similar operations within one's own organization.*
Competitive	This is a comparison and identification of *performance gaps* in relation to *the best of the direct competitors*.
Functional/ Industry	This is a *comparison of methods* to *organizations with similar processes in the same function* in search of better of world-class practices *of the same industry.*
Strategic	This refers to the *comparison of long-term strategies* and *general approaches* that have enabled high-performers to succeed. Strategic benchmarking involves considering high-level aspects such as core competencies, the development of new products and services, and improving capacity for dealing with changes in the external environment.
Generic	This is a comparison of work processes to others (non-competing organizations) who have innovative, exemplar work processes. The organizations to be benchmarked may or may not be in the same industry but the functions to be compared need to have some similarity.

2.3 Benchmarking process

There are several multistep approaches suggested by benchmarking experts (Camp 1995; Spendolini 1992, in Donthu et al., 2005). No single benchmarking process has been universally adopted, since various benchmarking methodologies kept on emerging (Adebanjo, Mann, BPIR, and COER). Among them are the 5-step approach (Mann, 2008), 6-step approach (Asian Productivity Organization, 2005), 10-step approach (Camp, 1995), 12-step approach (Codling, 1998, in Adebanjo et. al) and many others.

A survey conducted in 2004 of 227 organizations in 32 countries identified the various benchmarking models used by corporations (Adebanjo et al.). The top 9 benchmarking models (i.e. approaches) used, in order of frequency, were:

1. Developed own model (24%);
2. Robert Camp (13%);
3. Business Excellence Model, MBNQA (11%);
4. International Benchmarking Clearinghouse - APQC (10%);
5. Xerox 10-step model (10%);
6. Consulting Company provided (e.g. Arthur Anderson, Kaiser Associate, etc.) (9%);
7. National Guideline (e.g. CBI Probe, UK or Local Government Guides, Australia (5.5.%);
8. Benchmarking Centre (Sylvia Codling) (4%);
9. Kaplan's Scorecard (2.5%)

However, of all those differences in approaches, the basic steps of benchmarking that analysts agree on (Donthu et al., 2005):

1. Identify the best performers;
2. Set benchmarking goals; and
3. Implementation

2.3 Data Envelopment Analysis

Firstly introduced by Charnes et al. in (1978, in Donthu et al., 2005), data envelopment analysis (DEA) is used as an evaluation tool to measure and compare a decision making unit's (DMU's) productivity.

> The DEA is a method for mathematically comparing different DMUs productivity based on multiple inputs and multiple outputs. The ratio of weighted inputs and outputs produces a single measure of productivity called relative efficiency. DMUs that have a ratio of 1.0 referred to as efficient, given the required inputs and produced outputs (Charnes et al., 1978, in Angulo, 2006).

DEA is an extremal prediction method which estimates:

1. The minimum level of resources needed for a DMU, faced with a given environment, to produce a set of required outputs. This is known as the "resource conservation formulation" (Banker & Morrey, 1986a) or "input contraction" (Athanassopoulos and Giokas, 2000), and or
2. The maximum level of output possible to be generated by a DMU, given a set of resources, which is called "output augmentation" (Banker & Morrey, 1986a) or "output expansion" (Athanassopoulos and Giokas, 2000).

Later in 1985, Charnes et al. first suggested the application of DEA to gain insights into the efficiency of marketing efforts (Donthu et. al, 2005).

2.4 Benchmarking in marketing: marketing productivity

Marketers are interested in knowing the productivity (i.e. ratio of the outputs produced to the inputs used) of their relevant 'production' units, be it retail stores or individual sales people (Donthu and Yoo, 1998; Boles et al., 1995 in Donthu et. al, 2005). The need for measuring marketing impact is intensified as firms feel increasing pressure to justify their marketing expenditures (Gupta and Zeithaml 2005; Rust et al., 2004; Srivastha et al., 1998, in Angulo, 2006).

Charnes et al. (1985, in Boles & Donthu, 1995) first discussed the potential application of DEA to gain insights of marketing efforts (1985, in Donthu et al., 2005). It was since then that researchers attempted at making DEA as a mainstream tool for marketing practice (Donthu, 2005). Among them are (Donthu et al., 2005)

> Kamakura et al. (1988) who used DEA to measure welfare loss and market efficiency. Mahajan (1992) investigated operations in the insurance industry by comparing 33 different companies. Parsons (1990) examined DMUs wihtin a single company to identify the most efficient units. Boles et al. (1995) applied DEA to evaluate relative performance of salespeople and conclude that the analysis might prove useful in mentoring and training of salesforce based on the best practices of the most efficient salespeople. Kamakura and Ratchford (1996) evaluated multiple retail stores for their efficiency using DEA and translog cost function estimation, whereas Donthu and Yoo (1998) compared the results using DEA and regression. (pp. 1476)

In addition to the list, Jiang and Talaga (2006) explored the relationship between satisfying customers and building a customer base in the e-tailing industry using DEA. Angulo (2006) studied the marketing efficiency effect on long-term profits using a three stages methodology, two by econometric models and one using DEA.

Donthu et. al (2005) stated that despite its popularity among marketing practitioners in outstanding companies (especially those in Fortune 500 companies such as Xerox Corporation, AT&T, Chevron, American Express, and 3M), and marketing academics mentioning the benchmarking concept (Churchill & Peter, 1999; Kotler, 2000 in Donthu et al., 2005), they found there is no academic studies specifically dealing with benchmarking in marketing.

Their concern is that

> "as marketing plays an increasingly pervasive roles in firms' strategic decisions, benchmarking may be an important process for companies in imitating and learning from leading firms' marketing practices. While it is commonly accepted that in competitive environments only the best performers will survive in the long run, there is a dearth of research on the benchmarking of marketing productivity. There are no formal scientific benchmarking procedures that have been universally accepted in marketing" (Donthu et. al, 2005, pp. 1474).

They also found that there had not been any academic study *conceptualizing benchmarking* or *offering specific methodology* to assist marketing managers in their effort to benchmark marketing productivity.

For those reasons, they attempted to extend the applicability or benchmarking in marketing research and practice, by *suggesting the application of data envelopment analysis (DEA) to measure marketing productivity*. However, they stated that the suggestion of using DEA for benchmarking marketing productivity is within the assumption that *being efficient (or being the most productive) and wanting to emulate efficient firms* is the goal of all firms (Donthu et. al, 2005, pp. 1482).

CHAPTER 3

METHODOLOGY

3.1 Benchmarking Scope

The benchmarking study took the form of *internal benchmarking* (Camp, 1995), which refers to a company's efforts to examine best practices within a company's strategic business units or functions and try to transplant them to other parts of the company (Donthu et al., 2005).

3.2 Data Collection and Measurements

The data took form of a *panel data*, which is a data set containing observations on multiple phenomena observed over multiple time periods. From the consultation with the management, the inputs and outputs chosen to assess the supply chain productivity are *number of employees*, and *marketing fee* as inputs, and *additional sales,* and *sales revenue* as outputs[3].

Data were collected from 13 agencies within the South Jakarta domain for the period of July - October 2009. All of them were retrieved from the company's internal records. Below are the the detailed specifications of the efficiency measurements (i.e. input and output variables):

---

[3] The term inputs are outputs are used in DEA, of which the ratio of inputs and outputs produce a single measure of the outlets productivity (relative efficiency scores).

Table 3.1 Specifications of Data

Constructs	Item Label	Item wording	Indicators	Type of Data
Number of employees	Input1	Number of employees	number of persons	Secondary
Marketing Fee	Input2	Marketing Fee	monthly values in Rp.	Secondary
Additional Sales	Output1	Additional Sales	Number of subscribers	Secondary
Sales Revenue	Output2	Sales Revenue	monthly values in Rp.	Secondary

3.5 Analysis Tool: Data Envelopment Analysis

After the data were gathered, analysis was conducted using the *data envelopment analysis* (DEA) approach. The data processing was aided with the use of the software DEAP©. Using the DEA approach, this research aims to first analyze the relative marketing efficiency of each of the agencies.

The DEA first helps to determine which outlet is the most efficient given the *inputs* and *outputs* included within the computation, by first producing the *efficiency score*. The efficiency scores computed represent the best possible efficiency attainable by an outlet given its inputs and outputs, and comparing it to the inputs and outputs of the other peers in the group (Donthu *et al.*, 2005). Thus, the scores produced actually show *relative efficiency* rather than absolute efficiency scores.

Outlets with the best efficiency have the score of 1.0, while the rest possessing the score below 1.0 (< 1.0) are considered as relatively inefficient (Donthu *et al.* 2005). Those with the perfect efficiency score form a line of what is called the *DEA frontier*, whilst the inefficient ones are plotted below the DEA frontier line (see Figure 1.0).

The next step is to *choose the most inefficient* among the inefficient outlets (those with the efficiency scores below 1.0). The DEA computation then proceeds to identify the benchmarking 'role models' group of this particular most inefficient outlet, by producing the *facet/cone* of the DEA frontier. This 'cone' is formed by the best DMUs located along the frontier *closest* to the chosen outlet in efficiency, with the chosen inefficient outlet inside the cone body.

The distances between the chosen DMU with the frontier represent the *goals of the benchmarking* that need to be pursue by the chosen outlet in order to be efficient. Given for example in Figure 1.0, the unit A can choose to become more efficient by moving horizontally by X (reducing it inputs by X), or by moving vertically by Y (increasing it outputs by Y). The first is called *input contraction*, whilst the later is *output expansion* (Athanassopoulos and Giokas, 2000). The magnitude of the goals is also computed through the DEA computation.

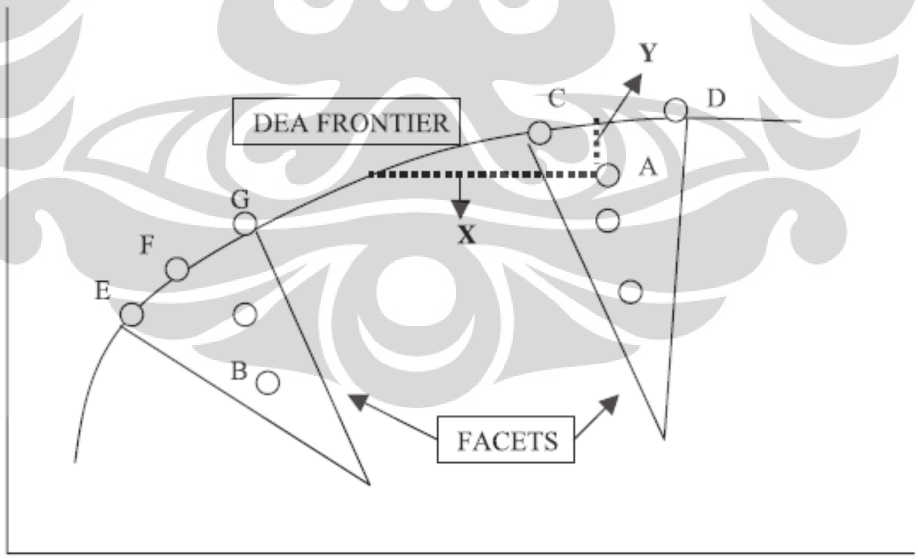

Figure 3.1 DEA Facets

Taken from Figure 2 in *Benchmarking marketing efficiency using data envelopment analysis*. Donthu, Hershberger, and Osmonbekov (2005).

3.6 DEA Model

The DEA model adopted for the research is the *output-orientated* model, which means the units are allowed to become efficient by focusing on output maximization. This consideration is based on the fact that the agencies are outsource parties. Therefore, we assume that the company has little control[4] over the inputs used[5]. On that account, the goal for each outlet is to maximize its efficiency by generating the most output possible in any mix (i.e. gaining as many subsribers, and generating as many revenue).

The output-orientated model is derived from the base DEA equation, with the objective to maximize the efficiency, h_o, for outlet o is:

$$\text{Max} \quad h_o = \frac{\sum_{r=1}^{s} U_r y_{ro}}{\sum_{i=1}^{m} V_i x_{io}} \tag{3.1}$$

Subject to:

$$\frac{\sum_{r=1}^{s} U_r y_{rj}}{\sum_{i=1}^{m} V_i x_{ij}} \leq 1 \tag{3.2}$$

for all $j = 1,\ldots,n$

$$U_i, V_i > 0 \tag{3.3}$$

$$r = 1,\ldots,s \tag{3.4}$$

$$i = 1,\ldots,m \tag{3.5}$$

---

4 In choosing whether to use input or output orientation method, essentially one should select according to which quantities (inputs or outputs) the managers have most control over (Coelli, p. 23, 2005).

5 Based on the consultation with the management, of the two inputs, the company is able to control the marketing fee allocated to each agencies. However, it isn't yet clear on how they determine the amount of the allocation.

Parameters:

n = number of outlets (i.e. DMUs) under analysis;
s = number of outputs under analysis;

m = number of inputs under analysis;

j = outlet (i.e. DMU) label;

r = output label;

i = input label;

y_j = vector of outputs for DMU_j with y_{rj} being the value of output r for DMU_j;

x_j = vector of inputs for DMU_j with x_{ij} being the value input i for DMU_j;

U_r = output weight to be estimated;

V_i = input weight to be estimated.

Hence, on the equation above, Y_{rj} and X_{ij} are the r^{th} output and i^{th} input observations for the j^{th} outlet. The efficiency computed by DEA assumes that 100% efficiency is attained for an outlet only when these conditions exist, which is referred to as *Pareto Optimality* (Donthu & Yoo, 1998, pp. 93):

1. None of the *outputs* can be increased without either increasing one or more *inputs,* or, decreasing some of its other *outputs*, and
2. None of the *inputs* can be decreased without decreasing some of its *outputs*, or, increasing some of its other *inputs*.

The output-orientated formula is presented below (Coelli, 2005)

Max h_o (3.9)

Subject to: $-h_o y_j + Y\lambda \geq 0$ (3.7)

$xj - X\lambda \geq 0$ (3.8)

$$N1'\lambda = 1 \tag{3.10}$$

$$\lambda \geq 0 \tag{3.11}$$

As we see above, X is the KxN input matrix, and Y is the MxN output matrix. Those represents the number of data from each DMUs. Thus N represents the number of DMUs.

The lambda is a Nx1 vector of constants. The efficiency value will satisfy the $h_o \leq 1$, with a value of 1 indicating a point on the frontier and hence a technically efficiect DMU, according to the Farrell (1957, in Coelli, 2005) defintiion. It should be noted that the linear formula must be solved N times, once for each the DMU in the sample.

Donthu & Yoo (1998) further stated that if there is no absolute standard of efficiency, then we have to adopt a standard which refers to the levels of efficiency relative to known level of attained efficiency by other outlets in similar conditions. This means that 100% of efficiency is defined to have been attained by an oulet, only when *comparisons* with other outlets do not provide evidence of ineffiency in the use of any inputs, and, in creation of any outputs.

3.7 Analysis steps

The DEA analysis is done by identifying the benchmarks (the role model among the units), then setting goals for improvement for the other less efficient units. To summarize, the DEA analysis steps of the research is (Donthu et al., 2005):

1. Determine inputs and outputs variable
2. Assign weights to the all inputs and outputs (this is done automatically through the software computation)
3. Compute *efficiency scores,* or the relative productivity (which represents the best possible effiency attainable by an outlet given its

inputs and outputs compared to the input and output of the rest of the other units).

4. Choose units with perfect efficiency score of 1.0 (i.e. the most efficient), which are be the ones lying on the DEA efficient frontier.
5. Identify the least inefficient unit
6. Identify the "role models" for the least efficient unit identified, which would create the "facet/cone".
7. Set goals for improvement. This is done by identifying the targets of the least efficient unit. The unit can become more efficient by reducing its inputs, or increasing its output.

In addition, we also conducted between agencies comparisons using Kruskal-Wallis test, and aggregate four months comparisons using both Friedman Rank and Kendall's W test. The analysis was aided by the data envelopment analysis software, DEAP© version 2.1[6], and statistical software SPSS 17.0©.

[6] DEAP© was developed by Prof. Timothy "Tim" Coelli. The complete package of the software and the guideline can be downloaded for free from http://www.uq.edu.au/economics/cepa/deap.htm

CHAPTER 4

ANALYSES, RESULTS, AND DISCUSSION

4.1 The Efficiency Scores: CRS, VRS, and SE

First of all, we provide the overall efficiency score, which is known as the *technical efficiency (TE)*. Farrell (1957, in Coelli, 2005) explained that technical efficiency reflects the ability of a firm to obtain maximal outputs from a given set of inputs. In the output-orientation model that we adopted, the technical efficiency was calculated using the *constant return to scale (CRS)* assumption. This means the model assumes that the output generated changes in the same proportion with the change in input. Therefore, from this point we use "CRS-TE" to refer to technical efficiency. The result of the agencies CRS-TE are presented in Table 4.1 below.

Table 4.1 CRS-Technical Efficiency Scores

No	Agency ID	*CRS-Technical Efficiency*				
		July	August	Sept	October	Agency Average
1	A	0.92	0.96	0.98	0.96	0.95
2	B	1.00	1.00	1.00	1.00	1.00
3	C	0.97	1.00	1.00	0.98	0.99
4	D	0.98	1.00	0.97	1.00	0.99
5	E	0.74	0.81	0.68	0.75	0.75
6	F	0.95	1.00	1.00	0.92	0.97
7	G	0.92	0.98	0.98	0.97	0.96
8	H	0.96	0.97	0.99	0.97	0.97
9	I	0.96	0.98	0.96	1.00	0.97
10	J	1.00	0.98	1.00	0.88	0.97
11	K	0.77	0.84	0.96	1.00	0.89
12	L	0.35	0.50	0.67	0.89	0.60
13	M	n/a[b]	n/a[b]	0.93	0.97	0.95
Monthly Average		0.88	0.85	0.93	0.95	0.92

a. The agency had not existed yet.

From the table we can see that, on average, agency B is the most efficient among the other twelve peers. It constantly holds a perfect relative efficiency score (i.e. a score of 1) for each of the five months. The least efficient unit is agency L (average efficiency score = 0.60).

However, the use of CRS assumption is only appropriate when *all* DMUs are operating at their *optimal* scales[7]. There are situations that may cause a DMU to be *not* operating at its optimal scale, such as financial constraints, imperfect competitions, etc. In such conditions, the DMU is said to be having an *inefficiency in scale*. The CRS assumption (i.e. when all DMUs are assumed to be operating at an optimal scale) is unable to show this. Its measure thus, is confused by the effect of scale. Therefore, to check whether any DMU has any scale inefficiencies (i.e. inefficiency due to the DMU's scale of production), we extend the analysis model to include the *variable return to scale (VRS)* assumption.

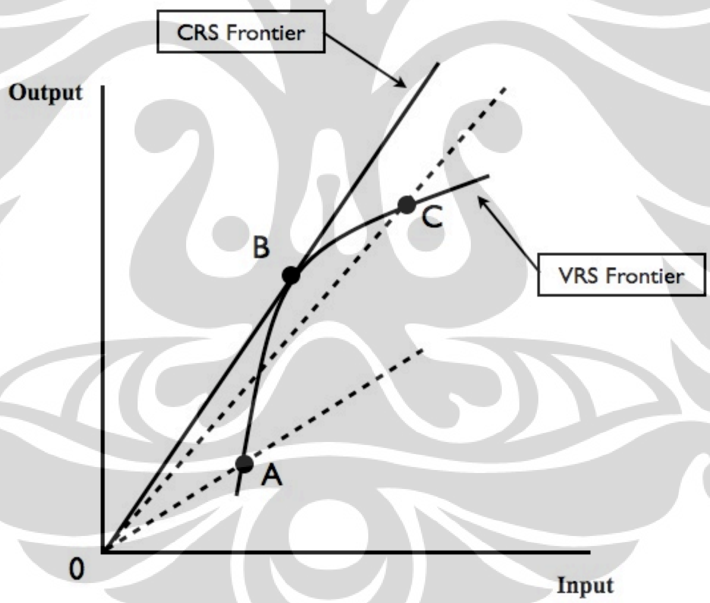

Figure 4.1 The Effect of Scale on Productivity

Taken and adjusted from Figure 3.9 in *An Introduction to Efficiency and Productivity Analysis.* Coelli (2008).

[7] A DMU is said to be operating at an optimal scale when it is in the position of the peak of the economies of scale condition, in which the average cost per unit of resource falls for the biggest proportion possible compared to the increase in production scale.

The VRS model separates the CRS efficiency score into two components: one that accounts for the "pure" ability of a DMU to obtain maximal output from a given set of inputs; one that shows how optimal the DMU production scale is. The first one is called the *"pure" technical efficiency*, which is measured by the VRS technical efficiency score ("VRS-TE")[8]. Here are the VRS-TE results for the agencies:

Table 4.2 VRS Technical Efficiency Scores

No	Agency ID	*VRS Technical Efficiency* July	August	Sept	October	Agency Average
1	A	1.00	1.00	1.00	1.00	1.00
2	B	1.00	1.00	1.00	1.00	1.00
3	C	1.00	1.00	1.00	1.00	1.00
4	D	0.98	1.00	0.98	1.00	0.99
5	E	0.75	0.82	0.68	0.76	0.75
6	F	0.96	1.00	1.00	0.93	0.97
7	G	0.94	0.99	0.99	0.97	0.97
8	H	0.98	1.00	1.00	1.00	0.99
9	I	0.96	0.98	0.98	1.00	0.98
10	J	1.00	1.00	1.00	0.94	0.99
11	K	0.78	0.84	0.96	1.00	0.90
12	L	0.35	0.50	0.68	0.90	0.61
13	M	n/a	n/a	0.94	0.99	0.96
Monthly Average		0.89	0.93	0.94	0.96	0.93

Now, if we observe the VRS-TE scores, there are agencies whose scores are different from their CRS-TE. When this happens, that indicates that the agency has a scale inefficiency. On the other hand, those who have the exact similar score among the two measures, are considered already scale efficient.

Henceforth, the effect of scale has been excluded. The VRS-TE score thus solely shows how well the agencies are in gaining the most output from the set of inputs in their hands. Under the VRS-TE assumption (i.e. based on how well they gain the most output from the use of inputs), agencies A, B, and C are shown to be

[8] From this point, we will refer to the previously technical effiency as "pure technical efficiency" or VRS-TE.

the most technically efficient among the peers. The least efficient one is, once again, agency L (VRS-TE score = 0.61).

The latter measure is known as *scale efficiency*. A scale efficiency measure can be used to indicate the amount by which productivity can be altered by moving to the point of the technically optimal productive scale (point B at Figure 4.1). A DMU which are not scale efficient could either scale down its operation when it's in the *decreasing return to scale*[9] condition ("DRS", from point C to B in Figure 4.1), or scale up when it's in *increasing return to scale* condition ("IRS", from point A to B in Figure 4.1) to become more productive.

The scale efficiency scores of the agencies are provided below.

Table 4.3 Scale Efficiency Scores

No	Agency ID	*Scale Efficiency* July		Aug		Sept		Oct		Agency Average
1	A	0.92	drs	0.96	drs	0.98	drs	0.96	drs	0.95
2	B	1.00	-	1.00	-	1.00	-	1.00	-	1.00
3	C	0.97	irs	1.00	-	1.00	-	0.98	irs	0.99
4	D	1.00	-	0.99	drs	0.98	drs	1.00	-	0.99
5	E	0.99	irs	0.99	drs	0.99	drs	0.99	irs	0.99
6	F	0.98	irs	1.00	-	1.00	-	0.99	irs	0.99
7	G	0.98	irs	0.99	drs	0.99	drs	1.00	-	0.99
8	H	0.98	irs	0.99	irs	0.99	irs	0.97	irs	0.98
9	I	0.99	drs	0.99	drs	0.99	drs	1.00	-	0.99
10	J	1.00	-	0.98	drs	1.00	-	0.93	drs	0.98
11	K	0.99	irs	0.99	drs	0.99	drs	1.00	-	0.99
12	L	0.99	irs	0.99	drs	0.98	drs	0.99	drs	0.99
13	M	n/a		n/a		0.99	drs	0.98	irs	0.98
Monthly Average		0.98		0.99		0.99		0.98		0.99

The average of the agencies scale efficiency are 0.99 over four months. This indicates that generally the agencies were operating quite close to optimal scale.

[9] As explained before, the concept of DRS and IRS relate to the economies of scale concept.

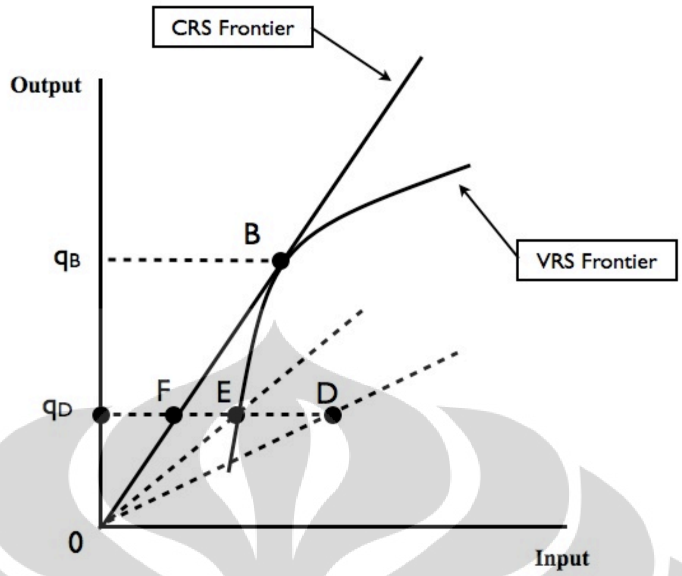

Figure 4.2 Scale Efficiency

Taken and adjusted from Figure 3.10 in *An Introduction to Efficiency and Productivity Analysis*. Coelli (2005).

We provide an illustration of the three measures in Figure 4.2. Suppose there is firm D with the production line of 0D. It can become more technically efficient by using less input to produce the same amount of output q_D (moving from point D to point E on the VRS frontier). Thence, this remove the technical inefficiency. However, at this point, unit D is still scale inefficient. It can further be improved by increasing its production scale to produce q_B (moving from point E to point B along the VRS frontier), and thus, removing the scale inefficiency. How to prove this? Look again at the figure. It is obvious that by adopting the production function of 0B, has bigger output-to-input ratio than the other two lines (alternatively it can be observed by the difference in slope[10]).

The mean score for the three measures over four months period are summarized in Table 4.4. As much as ten agencies (77%) performed above average technically (above the average VRS-TE of 0.93).

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[10] To gain deeper understanding, refer to a more detailed explanation on page 61 in Coelli's book *An Introduction to Efficiency and Productivity Analysis (2005).*

Table 4.4 Average Efficiency Scores from July - October 2009

No	Agency ID	Mean CRS-TE	Mean VRS-TE	Mean SE
1	A	0.96	1.00	0.96
2	B	1.00	1.00	1.00
3	C	0.97	1.00	0.97
4	D	0.99	0.99	1.00
5	E	0.71	0.75	0.99
6	F	0.97	0.97	0.99
7	G	0.95	0.97	0.99
8	H	0.95	0.99	0.95
9	I	0.98	0.98	1.00
10	J	0.92	0.99	0.93
11	K	0.91	0.90	0.99
12	L	0.68	0.61	0.99
13	M	0.95	0.96	0.77
Mean Score		0.92	0.93	0.96

Throughout the analysis period of July - October 2009, on average, the agencies who are fully scale efficient are agencies B, D, and I. Nevertheless, agency B is shown to be the most efficient generally. Three agencies--agency A, B, and C--are generally technically efficient. Among the peers, agency L shows the least efficiency performance over four months. However, if we observe the movement of its scores, it keeps on improving itself month by month (see Table 4.2). Thus, the low mean efficiency scores of agency L were affected mostly by its low performance for the first two months. We may therefore say that agency E is the least efficient among the thirteen, overally, as it hasnt showed much of improvements in its efficiency over the months (see again Table 4.2).

The recent position[11] of the efficiency can be observed from October result (see Table 4.5 below). Nine agencies (69%) technically performed above the average efficiency of 0.96. Seven agencies--A, B, C, D, H, I, and K--are shown to be the most fully technically efficient among the peers (see the VRS-TE scores). Nonetheless, among them, three agencies--A, C, and H--are still scale inefficient. Agency E is the least efficient in October, with a score of 0.76.

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[11] Within this paper, the month October of 2009 is considered the recent position corresponding to latest data available during the research.

Table 4.5 Efficiency Scores for October 2009

No	Agency ID	October CRS-TE	October VRS-TE	October SE	
1	A	0.96	1.00	0.96	drs
2	B	1.00	1.00	1.00	-
3	C	0.98	1.00	0.98	irs
4	D	1.00	1.00	1.00	-
5	E	0.75	0.76	0.99	irs
6	F	0.92	0.93	0.99	irs
7	G	0.97	0.97	1.00	-
8	H	0.97	1.00	0.97	irs
9	I	1.00	1.00	1.00	-
10	J	0.88	0.94	0.97	drs
11	K	1.00	1.00	1.00	-
12	L	0.89	0.90	0.99	drs
13	M	0.97	0.99	0.98	irs
Mean Score		0.95	0.96	0.99	

How much can they improve their efficiencies? DEA papers often report CRS-TE score since it provides a measure of the overall (aggregate) productivity improvement that is possible for a unit, *if* it is able to alter its scale of operation. Given that a firm is usually unable to alter its operation in the short run, one could view the ***VRS-TE score as a reflection of what can be achieved in the short run and the CRS-TE score as something that relates more to the long run*** (Coelli, 2005).

Thereby, for instance, the quickest way for agency E to be able to get into the efficiency frontier is to first improve its technical efficiency by 24% in the short run. Hence, agency E should gain more subcribers and yield more revenue with the current input sets[12]. Afterwards, when possible, agency E can further improve its efficiency by increasing its operation scale by 1%, to move up from its IRS position (see again explanation on Figure 4.2 on scale efficiency).

[12] We provide the exact value of how much the agencies should improve (i.e. the target) in the next section.

4.2 The targets: how much exactly do they have to improve?

We have arrived at the point to identify how much the inefficient agencies must improve in order to be in the efficiency frontier. DEA is able to calculate the amount by which an input or output must be improved for the less inefficient unit to become efficient. These amounts are then become the *target for improvements* for each of the inefficient agencies.

The targets calculated by DEA is generated by two components. The first one is obtained from the *radial inefficiency* of the unit, and the latter is the input or output *slacks*. These concepts are depicted in Figure 4.3, using a two-input, one output example for the sake of simplification.

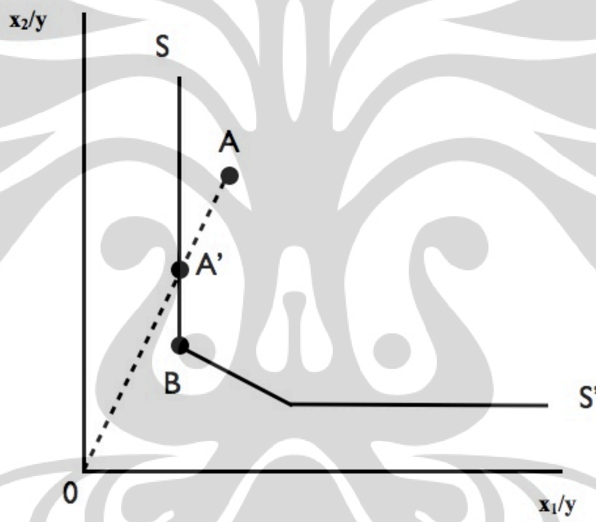

Figure 4.3 Radial and Slack movement

Taken from Figure 6.1 in *An Introduction to Efficiency and Productivity Analysis.* Coelli (2005).

Suppose there is a firm with several DMUs who produce the output y, with inputs of x_1 and x_2. The DMUs that are using the input combinations B and C are the efficient DMUs that form the frontier SS', and the DMU A is the inefficient unit. The technical inefficiency of DMU A relates to the distance of which all inputs can be proportionally reduced without a reduction in output (Coelli, 2005).

This is usually expressed in the percentage term of the ratio of A'A/0A[13], which represents the percentage by which all inputs could be reduced. Improving its productivity from point A to A' is what is called by improving *radially.*

Nonetheless, it is questionable whether point A' is already the efficiency point, since moving further to point B along the frontier will lead DMU A to use less of the input x_2 (by the amount of A'B) while still producing the same level of y. This excess amount of input x_2 used is known as the *input slacks*. Hence, ***the final target of improvement for DMU A, is to reduce the input usage into the combination of point A', and further reduce the usage of input x_2 by the amount of A'B***. The same concept also applies for the possibility of producing more output without using any more inputs, i.e. the *output slack.* Thus, in other words, the slack is the excess input or missing output that exists even after the proportional change in the input or the outputs.

The detailed October result of each of the agency's targets (under the term "projected value"), also with each of the radial and slack components are presented in Table 4.6. Take for instance, agency E for discussion, since it is the least efficient for the month.

Since we adopted the output orientation model, the projected targets relevant are the outputs (sales and revenue). With the current input sets, agency E is actually ***capable of gaining a total of 29 more in additional subscribers*** (a value of 26 subcribers from radial movement, and 3 from slack movement). Furthermore, it is ***also capable of earning Rp. 1,634,037 more in revenue***.

The result also indicates the peer (i.e. role models for agency E). The closest peers in order of importance are agency I, and agency C. The relative weights of these peers, respectively, is 0.53 and 0.47. Similar interpretation can also be applied to the rest of the peers.

Unfortunately, the targetted results presented only cover for the technical efficiency targets. The DEA model we adopted is unable to generate the result for

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13 The technical efficiency of DMU A is commonly measured by the ratio of 0A'/0A, which is equal to 1 minus A'A/0A. This is Farrell's (1957) measure of technical efficiency (Coelli, 2005)

scale efficiency target. Such target, however, is able to be revealed through other methods, such as the returns to scale estimation method[14]

[14] If you are interested on the method, you may want to read Zhu's article on *Setting scale efficient targets in DEA via returns to scale estimation method (2000).*

Table 4.6 Agency to agency results[a,b]

Results for agency:		A		
Technical efficiency		1		
Scale efficiency		0.961 (drs)		
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	513	0	0	513
Revenue	23,834.92	0	0	23,834.92
Employee	45	0	0	45
Mkt. Fee	47.61	0	0	47.61
LISTING OF PEERS:				
peer	lambda weight			
A	1.000			

Results for agency:		B		
Technical efficiency		1		
Scale efficiency		1.000 (crs)		
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	284	0	0	284
Revenue	12,591.22	0	0	12,591.22
Employee	11	0	0	11
Mkt. Fee	25.29	0	0	25.29
LISTING OF PEERS:				
peer	lambda weight			
B	1.000			

Results for agency:		C		
Technical efficiency		1		
Scale efficiency		0.983 (irs)		
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	2	0	0	2
Revenue	66.53	0	0	66.53
Employee	3	0	0	3
Mkt. Fee	0.18	0	0	0.18
LISTING OF PEERS:				
peer	lambda weight			
C	1.000			

Results for agency:		D		
Technical efficiency		1		
Scale efficiency		1.000 (crs)		
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	221	0	0	221
Revenue	11,637.65	0	0	11,637.65
Employee	25	0	0	25
Mkt. Fee	19.80	0	0	19.80
LISTING OF PEERS:				
peer	lambda weight			
D	1.000			

Results for agency:		E		
Technical efficiency		0.756		
Scale efficiency		0.997 (irs)		
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	80	26	3	109
Revenue	5,059.65	1,634	0	6,693.69
Employee	15	0	-3	12
Mkt. Fee	11.16	0	0	11.16
LISTING OF PEERS:				
peer	lambda weight			
I	0.530			
C	0.470			

Results for agency:		F		
Technical efficiency		0.926		
Scale efficiency		0.998 (irs)		
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	15	1	0	16
Revenue	567.79	45	0	613.14
Employee	7	0	-3	4
Mkt. Fee	1.44	0	0	1.44
LISTING OF PEERS:				
peer	lambda weight			
K	0.026			
B	0.040			
C	0.934			

a. The Revenue is measured in thousands of Rp. (Rp. 000)
b. The Marketing Fee is measured in millions of Rp. (Rp. 000,000)

(Table 4.6 continued)

Results for agency:		G		
Technical efficiency			0.968	
Scale efficiency			1.000 (crs)	
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	61	2	0	63
Revenue	2,101.14	68	0	2,169.60
Employee	15	0	-9	6
Mkt. Fee	5.58	0	0	5.58
LISTING OF PEERS:				
peer	lambda weight			
K	0.191			
B	0.139			
C	0.671			

Results for agency:		H		
Technical efficiency			1	
Scale efficiency			0.974 (irs)	
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	5	0	0	5
Revenue	31.05	0	0	31.05
Employee	3	0	0	3
Mkt. Fee	0.45	0	0	0.45
LISTING OF PEERS:				
peer	lambda weight			
H	1.000			

Results for agency:		I		
Technical efficiency			1	
Scale efficiency			1.000 (crs)	
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	203	0	0	203
Revenue	12,560.35	0	0	12,560.35
Employee	20	0	0	20
Mkt. Fee	20.88	0	0	20.88
LISTING OF PEERS:				
peer	lambda weight			
I	1.000			

Results for agency:		J		
Technical efficiency			0.944	
Scale efficiency			0.932 (drs)	
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	389	23	0	412
Revenue	13,035.96	770	5,069	18,874.46
Employee	30	0	0	30
Mkt. Fee	39.15	0	-1	37.76
LISTING OF PEERS:				
peer	lambda weight			
B	0.441			
A	0.559			

Results for agency:		K		
Technical efficiency			1	
Scale efficiency			1.000 (crs)	
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	117	0	0	117
Revenue	1,996.89	0	0	1,996.89
Employee	15	0	0	15
Mkt. Fee	10.26	0	0	10.26
LISTING OF PEERS:				
peer	lambda weight			
K	1.000			

Results for agency:		L		
Technical efficiency			0.903	
Scale efficiency			0.990 (drs)	
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	279	30	0	309
Revenue	11,002.22	1,180	1,633	13,815.33
Employee	30	0	-15	15
Mkt. Fee	27.72	0	0	27.72
LISTING OF PEERS:				
peer	lambda weight			
A	0.109			
B	0.891			

Results for firm:		M		
Technical efficiency			0.994	
Scale efficiency			0.979 (irs)	
PROJECTION SUMMARY:				
variable	original value	radial movement	slack movement	projected value
Sales	91	1	0	92
Revenue	4,684.74	30	0	4,714.67
Employee	10	0	0	10
Mkt. Fee	8.37	0	0	8.37
LISTING OF PEERS:				
peer	lambda weight	peer	lambda weight	
B	0.088	I	0.066	
D	0.235	C	0.611	

4.3 Agencies comparisons: between and within

In this section, first we try to see whether there is a significant difference between each agency in their productivity over the course of months. Kruskal-Wallis test for several independent samples are used for this purpose. The null hypothesis tested was that there is no significant difference in productivity between the agencies. The result rejected the null hypothesis (the chi-square value exceeds the critical value of 26.217; the *p*-value of 0.1% is less than the critical value of 1%). We may conclude that ***the productivity between the agencies over four months of July - October 2009 is significantly different statistically***.

Table 4.7 Kruskal-Wallis Test Result

Test Statistics[a,b]

	Efficiency Score
Chi-Square	34.120
df	12
Asymp. Sig.	0.001

a. Kruskal Wallis Test

b. Grouping Variable: Agency

In addition, we also want to see whether the agencies productivity vary from month to month[15]. In which case, *may* roughly suggests changes[16] in their productivity. For the task, we used both the nonparametric Friedman test for related samples, and Kendall's W test to strengthen the conclusion. Both tested the null hypothesis that the agencies showed no significant difference in productivity from month to month throughout the four months period.

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15 Unfortunately for both of these tests, only 12 agencies were able to be included during the computation. This is due to the nature of Friedman and Kendall's W that all samples must have the same number of observations (i.e. it couldn't process imbalanced samples). Thus, agency M must be left out since it has less observation (in this case monthly data) than the other peers.

16 It will be much more interesting and robust to measure changes in productivity using total factor productivity (known as TFP) measures which is more suitable for productivity comparisons over time (see the discussion on *measuring productivity change* in Coelli, 2005). Unfortunately for this research, that option is empirically not feasible to take, which is subject to the incorporated limitations of the available data (especially the period of time).

With the resulting of both chi-squares exceed the critical value of 7.815, and supported by the *p*-values of less than the significance level of 5% (0.032), the null hypothesis is thus rejected. This concludes that ***throughout the four month period of July - October 2009, the agencies had shown statistically significant changes in productivity.***

Table 4.8 Friedman Rank Test Result

Ranks

	Mean Rank
Technical Efficiency July	1.71
Technical Efficiency August	2.88
Technical Efficiency September	2.75
Technical Efficiency October	2.67

Test Statistics[a]

N	12
Chi-Square	8.821
df	3
Asymp. Sig.	0.032

a. Friedman Test

Table 4.9 Kendall's W Test Result

Ranks

	Mean Rank
Technical Efficiency July	1.71
Technical Efficiency August	2.88
Technical Efficiency September	2.75
Technical Efficiency October	2.67

Test Statistics

N	12
Kendall's W	0.245
Chi-Square	8.821
df	3
Asymp. Sig.	0.032

CHAPTER 5

CONCLUSION & RECOMMENDATION

5.1 Analysis conclusion

At the end of the study, we conclude several facts:

a. Agency B is the most efficient among the peers. Thus, it may be considered as the role model for the other agencies.

b. Results have also shown that agency E is the least efficient among the thirteen.

c. It was initially observed that agency L showed has the least mean efficiency score over the period. However, we observed that this is due to its low performance for the first two months. It has been improving itself ever since.

d. In terms of the average efficiency during the period July - October 2009, 77% (10 out of 13) of the agencies technically performed above average. Three agencies--agency A, B, and C--are generally technically efficient. Meanwhile, those who are fully scale efficient are agencies B, D, and I.

e. In their recent performance (October 2009), as much as 69% (9 out of 13) of agencies technically performed above the average efficiency. Seven agencies--A, B, C, D, H, I, and K--are shown to be the most fully technically efficient. Nonetheless, among them, three agencies--A, C, and H--are still scale inefficient. Agency E is the least efficient in October, with a score of 0.76.

f. With the current input sets, agency E is actually capable of gaining a total of 29 more in additional subscribers. Furthermore, it is also capable of earning Rp. 1,634,037 more in revenue. This was compared to its closest peers in order of importance: agency I, and agency C, with the relative weights respectively 0.53 and 0.47.

g. Statistically, the productivity between the agencies over four months of July - October 2009 is significantly different.
h. By the same token, throughout the four month period of July - October 2009, the agencies had shown statistically significant changes in productivity.

5.2 How this study can benefit the company

It has been showed that DEA can help the management in identifying the best performers for benchmarking its internal units (in this case, the outsource supply source, the agencies), which is through the relative performance evaluation (i.e. in benchmarking relative productivity). The management can then use the best performing agency, agency B, to be compared against. This can be done such as by *conducting further analysis on how agency B operates*, what marketing practice they used in getting subscribers, etc. Afterwards, the management may want to consider to implement the practice of agency B on the less efficient agencies. Special attention should be put on *agency E*. It *should be analyzed further of why this agency has a relatively low performance compared to the others*.

We have demonstrated the procedures on how the DEA could serve as a management tool to identify units that are underperformed. The management may want *to adopt this procedure as a method to evaluate productivity* of the other supply force, other internal business units, or even the company as a whole on a continuous basis. For the agencies, especially, will help the management to observe and control the progress of the underperforming agencies.

Further use of the DEA result is as a consideration for the management to build, or improve, the *incentive system for the agencies*. Since we determined the goal for each outlet is to maximize its efficiency by generating the most output possible (i.e. sales, and revenue), the management may want to create an incentive program which may encourage the inefficient agencies to reach their target outputs.

5.3. Recommendation for the company

Should the company wish to use this DEA method to evaluate the agencies performance, one thing to put into concern is the choice of inputs and outputs. The *inputs and outputs should be chosen carefully* so as to make sure that those are the ones which really count to the unit productivity.

In addition, on this case of measuring agencies performance, its important to note that the employees are assumed to be composite. So, instead of using only one chunk of employee category, we suggest to *categorize the employees based on levels* to further advance and improve the analysis.

Furthermore, the management should also *consider to improve and adjust the internal information system* so as to record all necessary data for future productivity analysis. However, proper identification of the required data (i.e. inputs and outputs) should be conducted carefully beforehand.

5.3 Suggestion for future research

Future marketing students who are interested in measuring marketing productivity may want to consider to apply the use *total factor productivity (TFP)* methods (such as Malmquist TFP index, component-based measures, etc.) to measure the changes in productivity over a period of time[17]. This method is more suitable to observe the underlying reasons and whether improvement or decline in productivity happened over time. Nonetheless, special attention must be put in the empirical feasibility of the data to implement the method chosen. Moreover, to be able to identify the scale efficiency targets, one may wish to extend the analysis to adopt the *returns to scale estimation method* as suggested by Zhu (2000).

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[17] I highly recommend Coelli's book *An Introduction to Efficiency and Productivity Analysis* on this topic, as it provides incredible discussions over the matter.

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Appendix 1 The Agency Input Data

No.	Agency ID	Number of Employees (# of persons)				Marketing Fee (value in Rp.)			
		July	August	Sept	Oct	July	August	Sept	Oct
1	A	45	45	45	45	54,720,000	38,430,000	31,590,000	47,610,000
2	B	11	11	11	11	21,870,000	23,850,000	13,410,000	25,290,000
3	C	5	5	5	3	5,490,000	2,700,000	1,350,000	180,000
4	D	25	25	25	25	20,880,000	16,560,000	12,240,000	19,800,000
5	E	15	15	15	15	11,250,000	8,280,000	10,080,000	11,160,000
6	F	7	7	7	7	8,460,000	4,860,000	3,780,000	1,440,000
7	G	15	15	15	15	7,740,000	7,830,000	6,840,000	5,580,000
8	H	10	10	3	3	6,480,000	2,340,000	630,000	450,000
9	I	20	20	20	20	23,310,000	26,100,000	18,630,000	20,880,000
10	J	30	30	30	30	67,860,000	49,230,000	58,950,000	39,150,000
11	K	15	15	15	15	15,660,000	14,040,000	6,660,000	10,260,000
12	L	30	30	30	30	16,110,000	20,790,000	17,100,000	27,720,000
13	M	0	5	10	10	0	90,000	7,650,000	8,370,000

Appendix 2 The Agency Output Data

No.	Agency ID	Additional Sales (# of subscribers)				Revenue (value in Rp.)			
		July	August	Sept	Oct	July	August	Sept	Oct
1	A	577	423	347	513	203,725,176	101,622,572	49,277,345	23,834,921
2	B	251	271	149	284	108,855,489	70,610,039	25,500,891	12,591,223
3	C	61	31	15	2	21,317,403	7,504,224	2,758,198	66,532
4	D	235	186	134	221	86,150,368	50,275,121	19,710,801	11,637,646
5	E	96	77	76	80	36,017,654	16,532,774	12,906,249	5,059,646
6	F	92	54	43	15	32,206,865	15,466,389	6,126,400	567,790
7	G	82	88	76	61	26,816,470	17,917,274	10,158,200	2,101,144
8	H	71	26	7	5	21,867,706	5,280,877	1,164,036	31,049
9	I	256	291	200	203	87,067,848	67,525,704	20,206,552	12,560,348
10	J	751	549	588	389	236,707,114	118,801,854	81,560,929	13,035,955
11	K	139	134	72	117	42,913,480	30,653,712	11,074,183	1,996,892
12	L	64	118	129	279	17,963,065	22,869,426	15,636,985	11,002,215
13	M	0	0	80	91	0	0	13,020,256	4,684,742