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The Evaluation of Efficiency Performance in Fashion Industry: Application of Data Envelopment Analysis

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ABSTRACT

Every companies use many different inputs such as assets, employees, and materials to generate and to produce some outputs such as profits, revenue, market share, brand popularity, etc. This dissertation focused on a linear programming model used in performance evaluation of six international fashion brand's industries as of the year of 2012. The purpose of this dissertation is to determine the efficiency of each company compared to the peer competitors within others fashion brands. The technique used in this paper is called Data Envelopment Analysis (DEA). It is an approach based on data for evaluating the performance of a set of peer entities called Decision Making Units (DMUs) which convert multiple inputs into multiple outputs. The emphasis was on data selection and cleanup, mathematical approach behind the data envelopment analysis model, and the application of this model to the efficiency comparison.

Keywords: Efficiency performance, fashion brand, Data Envelopment Analysis

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Richard Christian Tanggara

10 June 2014

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CHAPTER ONE
INTRODUCTION

1.1 Research Background

Fashion industry is one of the most thriving and profitable industries in the world. The advent of globalization has led to greater penetration of fashion into the mind of individuals. Globalization affects the mindset of each individual in making the decision to purchase the goods they want to buy, especially in terms of fashion style. There are some factors need to be consider in fashion industry as the latest trends, models, quality of product, also brand image are important in this industries.

Some mega fashion shows are being held in many nations across the worlds which are generated considerable interest among the individuals. In a mega fashion show event usually displayed superior products each company to attract interest of every individual who saw and witnessed the event. Even in any event it is always possible some company use the famous people to be model even become brand ambassador to represent each fashion company. All new ideas and fresh always appear in every event held. This condition showed that competition in fashion industry can be said to be growing and getting tougher.

There are many famous brands in the fashion industry, such as Louis Vuitton, Burberry, Coach, Prada, Christian Dior, Ralph Lauren, and many other brands. Which every brand sell a similar product, among other bags, wallets, clothes, accessories, etc. They have different style and model from each other competitors, with an unique design and greatest quality of fashion style products.

In very fierce competition of the fashion industry needed a true and proper strategy which is expected to improve the efficiency and effectiveness of a company. Efficiency and effectiveness of the company will impact the performance and quality gains obtained the company itself. According to Wikipedia, “efficiency in general describes the extent to which time, effort or cost is well used for the intended task or purpose. It is often used with the specific purpose of relaying the capability of a specific application of effort to produce a specific outcome effectively with a minimum amount or quantity of waste, expense, or unnecessary effort.” While the effectiveness mean, “the capability of producing a desired result.” A simple way of distinguishing between efficiency and effectiveness is the saying, “Efficiency is doing things right, while

Effectiveness is doing the right things." This is based on the premise that selection objectives of a process are just as important as the quality of that process. More high level of efficiency and effectiveness that company can be reach mean that company can make more gains and profits both in productivity, employee performance, even necessary expenses in any corporate activity.

The Data Envelopment Analysis (DEA) approach can be used to looking the most effective and efficient strategy for each company. It considers how much efficiency could be improved, and ranks the efficiency scores of individual company. Consequently, this research will further discuss and analyze the performance of some famous fashion industry and propose conclusions and suggestions for fashion industry strategies to make a better decision-making for those companies in the future.

1.2 Research Objective and Contribution

The purpose this research is to know more about fashion industry competition. This study was to apply Data Envelopment Analysis (DEA) to rank higher efficiency of fashion brand industries, which are using a little input to create more output. This purpose was accomplished by analyzing the financial statement of six international fashion brand industries.

Based upon the research background and motivation above, the research objectives and contributions of this research study are as follows:

1. To investigate the performance of the decision making has been made by every fashion brand companies.
2. To compare efficiency performance of the decision making for every fashion brand companies.
3. To assisting the company for making better decision in the future.

1.3 Scope of the Study

This study will only discuss the decision making which has been created by the decision maker of each company from the financial statement aspect. Also this study will discuss for the effective and efficiency of six famous fashion companies in the world, which as Louis-Vuitton, Prada, Coach, Burberry, Christian Dior, and Ralph Lauren were be the subject of this dissertation because that six famous fashion brands above has more different segment market and different customer segmentation. They have more unique characteristic of customers which are willing to spend their money to buy the luxury goods.

1.4 Structure of Study

In order to meet the stated research objectives and systematically present this empirical work, the paper was structured as follows.

Chapter 1: Introduction

This first chapter will be introducing the dissertation start from background, motivation and the chosen topics of interest.

Figure 1-1 will shows the research structure flowchart of this study.

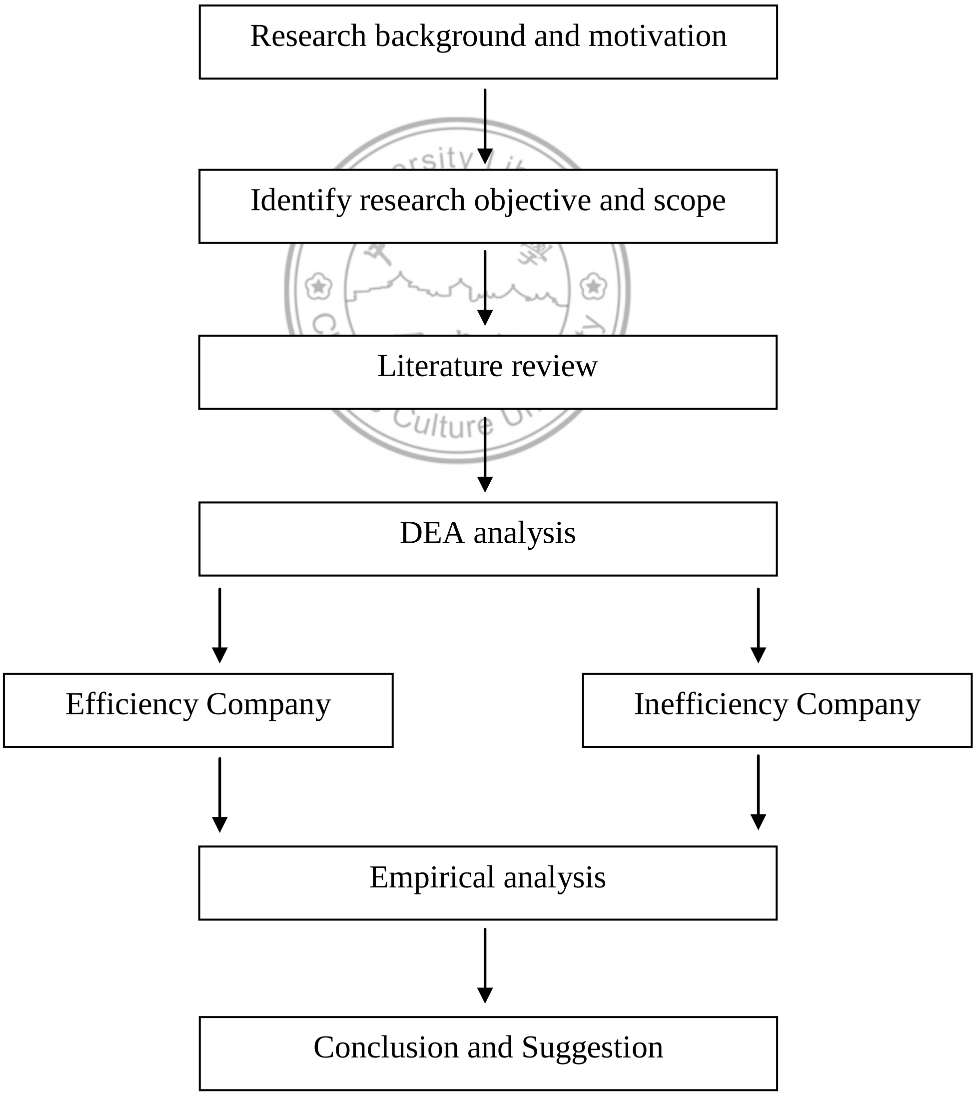

Figure 1-1 Research flowchart

Chapter 2: Literature Review

It is essential and crucial to understand previous studies and research which have written done before. It is taken from sources such as journals and books which in the similar topics with this dissertation. This chapter will be more focus on the reviewing of literatures on the topics of fashion industry sectors, design analysis performance and decision making performance.

Chapter 3: Research Design and Methodology

Research design and research methodology will be shown in this chapter. Research design will be presenting a research model which is proposed by suggesting the effect of each independent variable on dependent variable as well as the general relationship among the research construct. Research methodology is the methods and techniques were used to conduct this dissertation for investigating the case of data envelopment analysis measurement in the fashion design sector industry.

Chapter 4: Research Results

This chapter will be discussed about the research results and for theory implications.

Chapter 5: Conclusion and Suggestion

Significant findings, conclusions and suggestion for the research are summarized in this chapter.

CHAPTER TWO
LITERATURE REVIEW

2.1 Fashion

2.1.1 Definition of Fashion

According to Laver (1979) fashion was "a general term for a currently popular style or practice, especially in clothing, foot wear, or accessories. Fashion references to anything that is the current trend in look and dress up of a person."

Following to the statement above, fashion is symbolizes a latest trend especially in terms of clothing, hair style, accessories, and most everything that is used by every individual to show their identity to the public.

2.1.2 Fashion Life Cycle

According to Jie (2010) fashion usually has a larger cycle. It means fashion items that have been dropped and desirable in a long time might on one day will be return to trend and attract individual interest again. Moreover some fashion items that are considered timeless and never out of fashion. Jie (2010) explains in his statement, fashion life cycle can be divided into five parts:

a. Fashion Leadership

Fashion leadership is the period which an established fashion trend, general Europe was the center of every fashion trend that is formed. This is because so many fashion houses are routinely held fashion shows in each season, in this case for the for spring, summer, fall, or winter collection. Usually from this place a fashion trend created and then this fashion trend will start to spread throughout the world.

b. Increasing Social Visibility

As the early adopter from the fashion world, usually these people are the ones who have a high economic status. They are the early adopters and trendsetter for other people around the world. These people are usually referred to as fashion change agents which are consist of fashionistas, celebrities, leaders of certain social classes, and members of the social elite.

c. Conformity Within and Across Social Group

In this era, eventually all social classes will follow the trend that is set by the upper class.

d. Social Saturation

It is time that a fashion trend can be said at the level of its glory, this is because all social classes would be looking for items that are fashionable and trendy. And usually at this period some middle class of fashions brand also launched their product which is similar fashions collections or resemble the original goods (where the goods are initially available for the elite or upper social classes).

e. Decline and Obsolescent

As well as a product, in the end some of the fashion trend will decrease and eventually become obsolete or no longer desirable anymore.

2.2 Efficiency Performance Measurement

2.2.1 Performance

Both profit and non-profit organizations expect to receive the maximal output with the minimal input. The process to measure the performance between input and output is regarded as performance evaluation. Li and Kuo (2008) measured organizational performance with:

a. Financial Performance, including revenue growth rate, net income growth rate, and market share.
b. Operating Performance, containing product quality, degree of innovation, and value added.
c. Behavior Performance, covering staff turnover, employee morale, talent attraction, employee productivity, and employee's organizational commitment.

Li and Liu (2008) divided business performance into three parts, the first part is organizational effectiveness indicator, such as flexibility response, stability control, communication, and cohesion, the second part is financial indicator, including sales amount, cash flow, profit and return on equity (ROE), and the third part is Strategic indicator, containing market share and market growth rate.

Dyer and Reeve (1995) classified three output models for organizational performance, including:

a. Human resource output, covering rates of absenteeism, turnover rate, and group or individual performance.

b. Organizational output, such as productivity, quality, and service.

c. Financial and accounting output, covering return on asset (ROA) and Return on equity (ROE).

Research in fashion industry was numerous, but the performance analysis with DEA was insufficient. In consideration of the production theory, completeness of costs (including direct costs and indirect costs), and acquisition of data, assets and total operation expenses were selected as the input variables and net income and revenue were selected as the output variable for measuring the performance.

2.2.2 Performance Measurement

The nature of organizational performance and its measurement has been a topic for both scholars and practitioners since organizations were first formed. Kaplan (1992) developed the "balanced scorecard" approach to combines both historical accounting perspectives as well as operational measures that capture information about expected future organizational performance.

They have five perspectives of organizational performance to briefly examine organizational effectiveness and performance from the accounting, balanced scorecard, strategic management, entrepreneurship, and microeconomic perspectives.

a. The Accounting Literature Perspective

In measuring organizational performance, accounting scholars focus on the information content of the organization's financial statements and measures. Volumes of accounting rules and procedures have been developed over the years to make the information contained in organizational financial statements both meaningful and comparable over time across organizations.

Several conclusions are suggested, based upon this discussion of some of accounting research, on the information content of measures. First, the accounting profession, through the application of generally accepted accounting principles (GAAP) consistently applied, produces financial reports that are materially accurate, comparable across organizations in similar industries, and represent the execution on opportunities to date. Second, accounting reports provide important information about value creation that has been realized and retained in the company in the past. The accounting perspective of organizational performance is based upon past effect of managerial decision making and specially excludes the expected futures effect.

b. The Balance Scorecard Perspective

Kaplan (1992) proposed that effective organizational performance should be measured using a "balanced scorecard" which useful to attempt the bridge of the gap between theory and practice. Organizational performances measurement requires measures that are not purely financial in nature, because many of the financial indicators are result of critical operational measures. Balance scorecard measures include market share, change in intangible assets such as patents or human resources skills and abilities, customer satisfaction, product innovation, productivity, quality, and stakeholders performance. One critical weakness of the balanced scorecard approach is that it utilities operational measures that are unique to each organization.

c. The Strategic Management Perspective

Over the years, there have been many conceptualizations of organizations of organizational performance in the strategic management literature. Two critical aspects of organizational performance perspective in the literature are the constituencies for whom the organization performs, and the dimensions which should be measured.

d. The Entrepreneurship Perspective

The same problems that affect the strategic management perspective of organizational performance also affect the entrepreneurship perspective. It can be argued that the goals of the founding entrepreneur are the goals of the organizations. As with strategic management research, the entrepreneurship researchers adopt a multidimensional view of performance, recognizing that there are inherent tradeoffs between such issues as growth and profitability. With strategic management, the entrepreneurship perspective of performance is both multi-constituency and multidimensional.

e. The Microeconomic Perspective

Many scholars argued that owners of productive assets associate in an organization for the purpose of gaining economic advantage. The owner s of the assets will contribute them to the organization so long as the return they receive or expect to receive is satisfactory relative to the risk they take. Satisfaction is in part determined by the alternative uses that the owner has for the assets. In other words, the value that an organization creates for the owners contributed assets must be at least as large as the value expected. When the value created is less than the expected or required return, owners of assets will withdraw their support for the organization and put theirs assets to alternative uses where they can achieve the required return.

2.2.3 Efficiency Measurement

The first application of DEA was born out of the need to improve upon widely used but inadequate approaches to efficiency measurement. The first method, ratio analysis, is limited to single input and single output measurements. The basic measure of efficiency is the ratio between one input and one output also can be written as:

$$Efficiency = Output / Input \tag{2-1}$$

However, this equation is normally not adequate to be applied in the real world problems. There often have a numerous inputs and outputs of different categories, such as labor, time, money, etc. For a company, investors' concern would not limit one single output or input factor. Instead, investors pay highly attention to a lot of their financial information, including asset, liability, revenue, net income, as well as important financial ratios, including earnings per share, long-term debt ratio, liquidity ratio. One output or input can tell the information with respect to a certain field, but none of them can represent the overall financial performance of the company. An ideal way is to have all the major inputs and outputs information gathered together and develop a way to measure the efficiency of each company in terms of these factors, as well as flexible enough to put different constraints of weights. Therefore is not particularly useful for fashion industry and their multiple inputs and outputs. The second method, regression analysis, is able to handle multiple inputs and multiple outputs, however it estimates the average relationship between variables and this does not necessarily reflect the efficient relationship.

Unlike conventional methods such as ratio analysis and regression analysis, modern efficiency measurement techniques not only estimate a production frontier but also focused on providing an estimate of each observation's distance from the frontier in order to give an objective estimate of efficiency. There are two broad features that distinguish the alternative modern efficiency measurement techniques, whether they are parametric or non-parametric and whether they are deterministic or stochastic (Hollingsworth et al., 1999). Parametric methods assume a specific functional for the production function, whereas non-parametric methods do not and use empirical observations to infer the shape of the production frontier. Deterministic methods assume that entire distance of a unit from the frontier is due inefficiency, where stochastic methods assume that some of it is a due to random error. They have two of the most commonly used modern efficiency measurement, they are Stochastic Frontier Analysis and Data Envelopment Analysis.

Stochastic Frontier Analysis (SFA) is a parametric method that specifies the production function in a manner similar to regression analysis. However, in stochastic process they decompose the residual error term into inefficiency and random error. This is done by assuming that the inefficiency and random error components of the residual have different distributions. The random error component, which can be interpreted as random events outside of the control of the organization, is assumed to be distributed normally, whereas the inefficiency component is usually assumed to follow an asymmetric half-normal distribution. As with regression analysis, models with both multiple inputs and multiple outputs are methodologically challenging with SFA, and therefore the multiple inputs are often combined into a single cost function (Jacobs, 2006). SFA has been most commonly used to study the efficiency hospitals, nursing homes, pharmacies, and etc.

2.3 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) was developed by Charnes, Cooper, and Rhodes in 1978 in order to address the need for a non-parametric approach method that specifies the shape of the efficient frontier from observed data for multiple inputs and multiple outputs, and therefore place no restrictions on the form of the frontier. However, DEA is a deterministic process that assumes that the entire distance of a unit from the frontier is due to inefficiency.

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 (Cooper et al., 2000). Charnes et al. (1978) said the Data Envelopment Analysis (DEA) is a widely used optimization-based technique that measures the relative performance of decision making units that are characterized by a multiple objective and/or multiple inputs structure.

Data Analysis Envelopment (DEA) also a technique used to assess the comparative efficiency of homogenous operating units, evaluating performance of many different kinds of entities engaged in many different activities in many different contexts in many different countries such as schools, hospitals, military operation, sales outlets, prison, and utility companies. The DEA approach does not require specification of any functional relationship between inputs and outputs, or a priori specification of weights of inputs and outputs. DEA will provide gross efficiency scores based on the effect of controllable and uncontrollable factors.

The DEA methodology measures the performance efficiency of organization units called Decision Making Units (DMUs). The technique aims to measure how efficiently a DMU uses the resources available to generate a set of outputs. The performance of DMUs is assessed in DEA using the concept of efficiency or productivity defined as a ratio of total outputs to total inputs. Efficiencies estimated using DEA are relative, that is, relative to the best performance DMU or DMUs.

The earliest DEA model, known as the CCR model, uses linear programming extensions to determine the optimal weighting of each input and output for each DMU being assessed, subject to the constraint that no other DMU could achieve greater than 100% efficiency by using the same weights (Coelli et al., 2000). In the CCR model *m* inputs (X_{1j}, X_{2j}, X_{3j}, …., X_{nj}) and *s* outputs (Y_{1j}, Y_{2j}, Y_{3j}, …., Y_{nj}) are selected for each DMU*j* (*j*=1, …., n) (Cooper et al., 2000). A linear programming model is then constructed that seeks to maximize the ratio of the total number of outputs to the total number of inputs, multiplied by the optimum weights for each of them. The resulting ratio, referred to by θ is scalar that is the efficiency score for that DMU. Efficiency score range between 0, for completely relatively inefficient DMUs, and 1, for completely relatively efficient DMUs. The model is the run *n* times, once for each DMU.

For the *jth* DMU the model can be expressed as follows:

$$Max\ \theta = \frac{u_1 y_{1j} - u_2 y_{2j} - u_s y_{sj}}{v_1 x_{1j} - v_2 x_{2j} - v_m x_{mj}} \tag{2-2}$$

$$\text{subject to (s.t.)}: \frac{u_1 y_{1j} - u_2 y_{2j} \; - u_s y_{sj}}{v_1 x_{1j} - \; v_2 x_{2j} - \; v_m x_{mj}} \leq 1 \; (j = 1, \ldots, n) \tag{2-3}$$

$$v_1, v_2, \ldots, v_m \geq 0$$

$$u_1, u_2, \ldots, u_s \geq 0$$

In addition to the constraint that the weights used for a DMU must not be able to make another DMUs efficiency score greater than 1.0, there are also non-negativity constraints for the input and output weights. This is the primal, or multiplier, form of the CCR model. The fractional linear programming dual problem can be directly derived from the primal problem.

As every iteration of the model optimizes the mix of inputs and outputs for each DMU, there is no need to specify the relationships ahead of time. An additional advantage of this method is the ability to account for multiple inputs and outputs that may be expressed in different units.

In 1984 Banker, Charnes, and Cooper modified the CCR model by adding a constraint for variable returns to scale. This convexity constraint causes the efficiency frontier to tighten into a more convex form around the DMUs (Coelli et al., 2000). Therefore, DMUs are benchmarked against others of comparable size.

The dual form of the BCC model can be expressed as follows:

Min θ_B (2-4)

Subject to: $\theta_B x_j - X\lambda \geq 1 \; (j = 1, \ldots, n)$ (2-5)

$e\lambda = 1$

$\lambda \geq 0,$

Where λ is a vector of constants and e is a vector ones. This additional constraint is the main difference between the CCR and BCC models and is what causes the feasible region to be a subset of the CCR model frontier (Cooper et al., 2000).

2.3.1 General Applications of Data Envelopment Analysis (DEA)

Since enhanced efficiency or productivity often translates to saving with respect to time and money, DEA has been used quite extensively to evaluate the relative efficiency of container terminals throughout the world. For example, Cullinane et al. (2006) evaluated the relative efficiency of 26 container ports using DEA from two perspectives, deterministically (using an output oriented DEA model under both VRS and CRS) and stochastically (based on a log-linear Cobb-Douglas production function and under the error assumption of half-normal, truncated normal, and gamma distributions). Cullinane et al. found that while there were differences in the efficiency ranks of the two methods, those rankings were highly correlated. In addition, Cullinane et al. recognized the importance of these efficiency measures in that they could influence a port's decision making process and governmental policy making.

Similarly, Rios and Macada (2006) used DEA to evaluate the operational efficiency of 23 container ports within the Southern Common Market referred to as Mercosur (with member countries Brazil, Uruguay, Agentine, and Paraguay). Using the terminal area as well as the number of cranes, berths, employees, and yard equipment as inputs and the number of TEUs (i.e., quantify of a 20 foot container) moved and average number of containers moved per hour per ship as outputs, Rios and Macada found that the number of 100% efficient container ports had decrease based on previous studies of the same area. As a result of this alarming trend, Rios and Macada recommended that in order to improve their operational efficiency, the inefficient container ports identified using DEA use the efficient container ports as benchmarks.

Other application of DEA include the efficiency evaluation of quick service chained restaurants (Lan, Lan, Chang, and Chuang, 2006) and human resource departments for fire branches in Tainan County, Taiwan (Lan, Chuang, and Chang, 2007). In order to evaluate the performance of quick service chained restaurants with respect to recruitment and training of employees, Lan et al. (2006) utilized both BCC and CCR DEA models. By doing so, Lan et al.were able to accommodate the multiple inputs and outputs that are associated with these restaurants without having to make any prior assumptions about the data. After examining the results, Lan et al. recommended using the efficient restaurants as benchmarks and that any new employees be trained at the benchmark (i.e, efficient) restaurants. The study by Lan et al. (2007) illustrated the use of DEA to evaluate 35 fire branches within the Tainan Fire Bureau in Taiwan. Of those branches evaluated, 21 were considered to be technically efficient. Using this information as a basis, Lan et al. (2007) then went on to determine future output trends for resourcing purposes.

The flexibility of DEA and its applicability to many different disciplines is evidenced by more than 120 different models in use today (for a listing of the various

DEA models see Emrouznejad, 2001). For example, Forsund and Zanola (2006) used DEA to evaluate the transformation of art pieces into auction bids while Chen et al. (2006) used a DEA game model to evaluate the efficiency of supply chains. By modifying the DEA model to include variables that represented risk and uncertainty, Wu (2010) evaluated the supply chain from the perspective of efficiency or performance of the suppliers. Womer, Bougnol, Dula, and Retzlaff-Roberts (2006) used alternatives as the DMUs, costs as the inputs, and benefits as the outputs in the DEA model in order to perform a benefit-cost analysis of a highway construction project in Memphis, Tennessee. Pergelova et al., (2008) used both DEA and stochastic frontier analysis (SFA) to evaluate the efficiency of marketing automobiles in Spain with respect to offline and online delivery methods. Similarly, Von et al. (2006) used DEA and SFA to assess the efficiency or productivity of 307 electric companies in Germany while Khodabakhshi et al. (2010) used a chance-constrained DEA model to develop a stochastic super-efficiency model for the purpose of evaluating the efficiency of 17 electrical distribution companies in Iran. Khodabakhshi et al. (2010) next applied their stochastic super-efficiency DEA model to the efficiency assessment of United States public banks and thrifts CEOs.

The discipline of higher education has also benefitted from the use of DEA. For example, Tauer, Fried, and Fry (2007) used DEA to determine efficiency with respect to the educational and research performance of 26 individual departments within the Agriculture and Life Sciences College of Cornell University. Recognizing that departments operating on the efficient frontier are considered to be the best practicing departments and peers to the inefficient departments, Tuaer et al. also realized that the efficiency evaluation was limited by the data itself with respect to the number and selection of departments or DMUs in the study. In addition, the number and type of inputs and outputs will affect the DEA results. Thus to be thorough, Tauer et al. evaluated 16 DEA models with varying inputs and outputs and found that some departments' technical efficiency remained high regardless of the model, while other departments' technical efficiency varied across the different models. Thus, in order to obtain a more holistic view of departmental performance, Tauer et al. recommended incorporating various qualitative factors with the DEA results.

In another application of DEA to measure the efficiency of university departments, Leitner et al. (2007) examined science departments in Australian universities. Using input-oriented CCR and BCC models, Leitner et al. used correlations and ordinary least squares to determine which input and output variables to include, ultimately resulting in one input and 12 output variables. The resulting analysis showed that half of the departments evaluated were relatively efficient. The most interesting result was the effect of the economies of scale on departmental efficiency. Leitner et al. showed that departmental size directly impacts performance with respect to efficiency, with smaller and larger departments being more efficient than mid-size departments. Leitner et al. also showed with the DEA results that teaching performance and research performance were directly related.

CHAPTER THREE

RESEARCH DESIGN AND METHODOLOGY

This chapter will be describes the conceptual model of Data Envelopment Analysis (DEA), the methodology used to evaluate the efficiency of six fashion industry companies, whereas Burberry, Coach, Prada, Louis-Vuitton, Prada, Ralph Lauren, and Christian Dior as the subject observation. After some general background information, the basic concepts of DEA are illustrated graphically. This is followed by the presentation of various mathematical formulations, and finally, some properties and extensions of the basic DEA formulations are discussed.

3.1 Data Envelopment Analysis (DEA) Background

Data Envelopment Analysis (DEA) is a fractional linear programming technique that can be used to rank and compare the relative performance of various entities (inputs or outputs), termed decision making units (DMUs). It was initially developed by Charnes, Cooper, and Rhodes in 1978 as a method for evaluating publicly funded programs, but now this technique also has been applied to many industries like financial services (banks, insurance), health care (hospitals), military services, education institution (schools, universities), ports, railways, and many more high technology industry sectors. Unlike many statistical approaches that measure units relative to the average, DEA just take an extreme point technique that will be compares DMUs with only the best performers.

Founded on Farrell's concept of productive efficiency (Farrell, 1957), who defines two measures of efficiency for a firm, The first is *technical efficiency*, which conforms to traditional measures of efficiency and measures a firm's ability to produce maximal output from a given level of inputs. The second is *price efficiency* or *allocative efficiency* and measures the degree to which a firm uses the production inputs in the optimal proportions in view of their individual prices. Farrell combines these two efficiency measure to determine the *overall efficiency* of the firm. In order for the firm to be efficient overall, it must exhibit both technical and price efficiency (Farrell, 1957).

In the original DEA model, Charnes, Cooper, and Rhodes proposed measuring the technical efficiency of a DMU as the maximum of a ratio of weighted outputs to weighted inputs. Each DMU can choose its own input and output weight in order to give it the best possible efficiency score, subject to the condition that corresponding ratio for every DMU be less than or equal to unity (Charnes et al., 1978). The DMUs under analysis must be comparable, in that they use the same set of inputs to produce the same set of outputs. It is mean, the DMU must be operated in similar environments, and this condition is different in the operating environment that must be accounted for.

3.2 Graphical Illustration

The basic concepts of DEA can be illustrated graphically with the simple single input and single output example will be represented below.

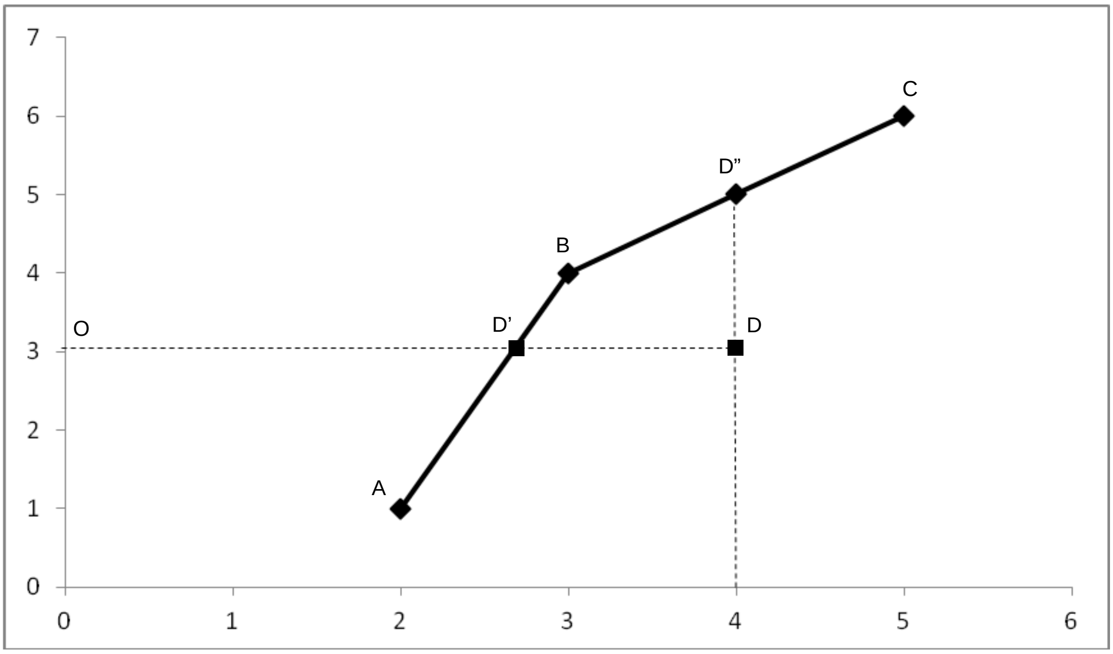

Figure 3-1 Single input and single output data envelopment analysis (DEA)

In Figure 3-1 explain there are four DMUs: A, B, C, and D. DMUs A, B, and C can be considered technically efficient because they each use a minimum amount of the input to produce various level of output. The DMU A, B, and C form the efficient frontier, which consists exclusively of the best performing units in the data set in converting inputs into outputs. This condition is totally different from DMU D, DMU D can be said not efficient because it uses relatively higher levels of inputs to produce the same level output as the others DMUs on the efficient frontier. The point D' is represented when DMU D reducing its input while maintaining a constant level of output, and the point D'' is represented when DMU D increasing its output while maintaining a constant level of input. With these two ways DMU D can become efficient because DMU D can manage well their input and output to get more efficient level.

From that figure DEA assigns all efficient DMUs (on the efficient frontier) a technical efficiency score of 1. The technical efficiency of inefficient DMUs can be measured by referring to their projected points on the frontier, and is a measure of the inefficient DMUs distance from the efficient frontier. The score of efficiency from DMU D can be calculated below.

Input Orientation:

$$\frac{OD'}{OD} = \frac{2.67}{4} = 0.67 \tag{3-1}$$

Output Orientation:

$$\frac{PD''}{PD} = \frac{5}{3} = 1.67 \tag{3-2}$$

From this calculation DMU D must either reduce its input to 67% of its current level which represented by *D'* or increase its output by 67% which represented by *D"*. In the input oriented model, the efficient of DMU D is evaluated by combination of DMUs A and B, whereas output oriented model, DMU D is evaluated by combination of DMU C and C.

Another type of inefficiency is called mix inefficiency its occurs when some, but not all of inputs and outputs exhibit inefficient behavior. Mix inefficient can be illustrated with the simple two inputs and one output below.

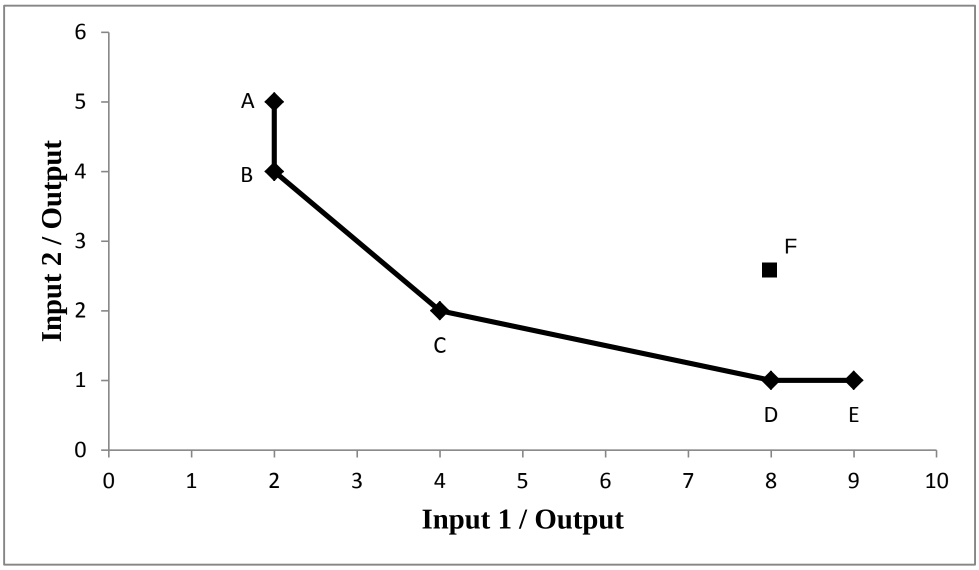

Figure 3-2 Two inputs and one output data envelopment analysis (DEA) example illustrating mix inefficiency

In this figure, the output has been unitized. DMUs A, B, C, D, and E all is lie on the efficient frontier and thus are technically inefficient DMU. For Example DMU A can produces the same level of output as DMU B using the same level of input 1, but relatively more of input 2. While technically efficient, DMU A is mix inefficient because its elimination alters the proportions in which inputs are utilized or the outputs are produced. This condition is similarly with DMU E when uses relatively more of input 1 than DMU D and it is also mix inefficient.

3.3 Mathematical Formulations

3.3.1 CCR Model

The basic and original of DEA model is CCR Model who introduced by Charnes, Cooper, and Rhodes and is built on the assumption of constant return-to-scale (CRS). Which if the inputs are changed by positive proportional factor and the outputs become increased by that same factor. (Mathematically, if a asset of inputs and outputs (x,y) represent a feasible activity within the set of feasible activities, then (tx,ty) is also feasible for any positive scalar t.)

For n DMUs, each with m inputs and s outputs, the CCR model is given by the following fractional program (Cooper et al., 2007) :

$$\text{Max} \qquad z_0 = \frac{\sum_{i=1}^{s} u_i y_{i0}}{\sum_{j=1}^{m} v_j x_{j0}} \tag{3-3}$$

$$\text{Subject to:} \qquad \frac{\sum_{i=1}^{s} u_i y_{ik}}{\sum_{j=1}^{m} v_j x_{jk}} \leq 1 \quad (k = 1, \ldots, n) \tag{3-4}$$

$$u_i \geq 0$$

$$v_j \geq 0$$

In this fractional program, y_{ik} represents output i for DMU k, x_{jk} represents input j for DMU k, whereas u_i and v_j represents the output and input multipliers. The fractional program can be converted into the following linear program, known as the multiplier form of the CCR Model:

$$\text{Max} \qquad z_0 = \sum_{i=1}^{s} u_i y_{i0} \tag{3-5}$$

$$\text{Subject to:} \qquad \sum_{j=1}^{m} v_j x_{j0} = 1 \tag{3-6}$$

$$-\sum_{j=1}^{m} v_j x_{jk} + \sum_{i=1}^{s} u_i y_{ik} \leq 0 \quad (k = 1, \ldots, n)$$

$$u_i \geq 0$$

$$v_j \geq 0$$

This linear program also has a dual envelopment form :

$$\text{Min} \qquad \theta - \varepsilon \left(\sum_{j=1}^{m} s_j^- + \sum_{i=1}^{s} s_i^+\right) \tag{3-7}$$

$$\text{Subject to:} \qquad \theta x_{j0} = \sum_{k=1}^{n} x_{jk}\lambda_k + s_j^- \quad (j = 1, \ldots, m) \tag{3-8}$$

$$y_{i0} = \sum_{k=1}^{n} y_{ik}\lambda_k - s_j^+ \quad (i = 1, \ldots, s)$$

$$0 \leq \lambda_k, s_j^-, s_i^+ \quad \forall k, i, j$$

The above representation of dual model employs a single objective function to represent a two stage problem. The first stage is to find the optimal value of θ and the second stage is to find the maximum sum of the input and output slacks (s^- and s^+). The dual model is preferred computationally over the linear programming model because it has fewer constraints, and it also provides a more intuitive solution.

There are various elements to the solution of the envelopment model is a measure of the DMU's technical (or radial) efficiency and represents the value by which the inputs must be proportionally reduced to project the DMU onto the efficient frontier and render it technically efficient. (A DMU with 8 = 1 is technically efficient as it already lies on the efficient frontier), s_j^- and s_i^+ are slack variables that represent, respectively, an excess in input *j* and a shortfall in output *i* (measures of mix inefficiency). To be fully efficient, a DMU must have an efficiency score of 1 with all slacks being equal to zero. A DMU with a technical efficiency score of 1 but containing non-zero slacks is referred to as *weakly efficient*. The λ's represent the linear combination of reference DMUs to which the DMU under analysis is being compared, with all non-zero λ_k's indicating that DMU *k* is a member of the reference set.

3.3.2 BCC Model

The BCC model was developed by Banker, Cooper, and Charnes in 1984 (Banker et al., 1984). The BCC model was born from the modification of the CCR. The two models are similar with the exception of the constraint regarding the weights. In the BCC model, this constraint is modified to incorporate frontier convexity associated with Variables Returns-to-Scale (VRS). The multiplier form of the BCC model is shown below (Cooper et al. 2007) :

Max $\quad z_0 = \sum_{i=1}^{s} u_i y_{i0} - u_0 \qquad (3\text{-}9)$

Subject to: $\quad \sum_{j=1}^{m} v_j x_{j0} = 1$

$$-\sum_{j=1}^{m} v_j x_{jk} + \sum_{i=1}^{s} u_i y_{ik} - u_0 \le 0 \quad (k = 1, \ldots, n) \qquad (3\text{-}10)$$

$u_i \geq 0$

$v_j \geq 0$

u_0 *is free in sign*

The BCC model also has a dual envelopment form :

$$\text{Min} \quad \theta - \varepsilon \left(\sum_{j=1}^{m} s_j^- + \sum_{i=1}^{s} s_i^+\right) \tag{3-11}$$

$$\text{Subject to:} \quad \theta x_{j0} = \sum_{k=1}^{n} x_{jk}\lambda_k + s_j^- \qquad (j = 1, \ldots., m) \tag{3-12}$$

$$y_{i0} = \sum_{k=1}^{n} y_{ik}\lambda_k - s_j^+ \qquad (i= 1, \ldots., s)$$

$$\sum\nolimits_{k=1}^{n} = 1$$

$$0 \leq \lambda_k, s_j^-, s_i^+ \qquad \forall k, i, j$$

The BCC model varies from the CCR model only in the presence of the free variable u_o in the multiplier form and the additional constraint Σλ = 1 in the envelopment form. The constraint Σλ = 1 is known as a convexity constraint which combines with the constraint $\lambda_k \geq 0$ to impose a convexity condition on the permissible ways in which the *n* DMUs can be combined. The variable u_o of the multiplier form identifies the returns-to-scale situation for a DMU on the efficient frontier. A positive *uo* is indicative of decreasing returns-to-scale, a negative u_o is indicative of increasing returns-to-scale, and u_o = 0 is indicative of constant returns-to-scale (Cooper, et al., 2007). However, under certain circumstances, multiple solutions may exist for the variable u_o. Sueyoshi has developed a method for determining the occurrence of multiple solutions based on comparing the number of multipliers with the number of binding constraints at optimality. When the former is larger than the latter, multiple solutions exist. Sueyoshi also offers two models for dealing with multiple returns-to-scale solutions. For further details, the reader is referred to (Sueyoshi, 1999).

Returning to the example of Figure 3-1, Figure 3-3 below will be shown the efficient frontiers of both the CCR model (broken line) and the BCC model (solid line).

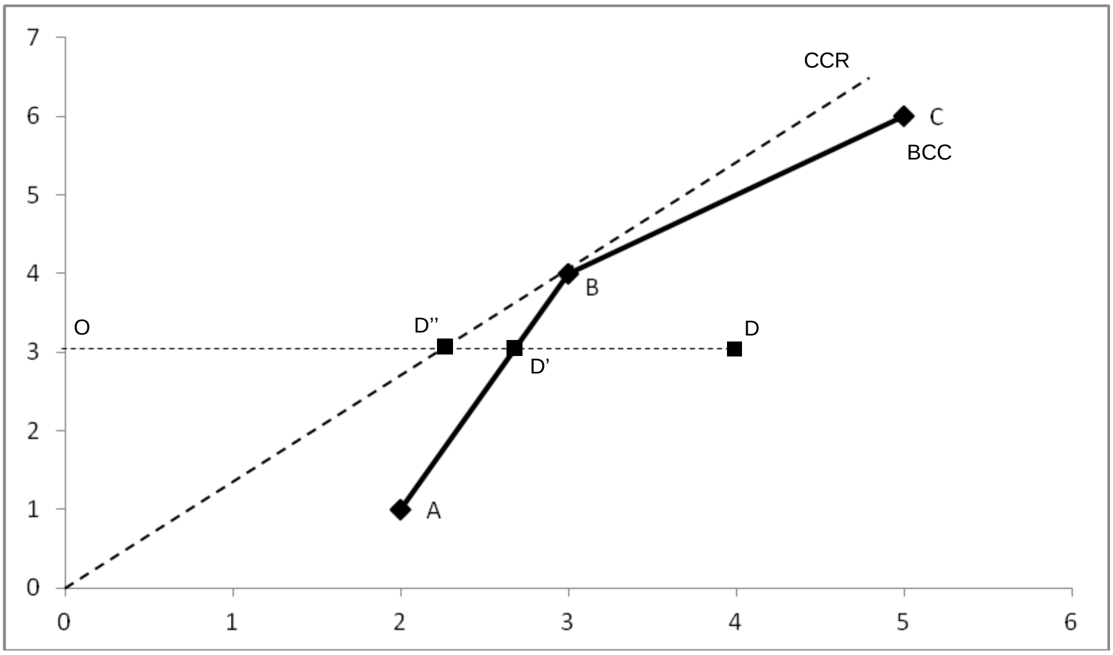

Figure 3-3 Single input and single output data envelopment analysis (DEA) examples illustrating CCR and BCC models

While DMUs A, B and C are all BCC efficient, only DMU B is CCR efficient. DMU D is neither CCR nor BCC efficient. The calculation below will be shown the (input-oriented) CCR and BCC technical score of efficiency from DMU D can be calculated below.

CCR Efficiency θ_{CCR}:

$$\frac{OD''}{OD} = \frac{2.25}{4} = 0.56 \tag{3-13}$$

BCC Efficiency θ_{BCC}:

$$\frac{OD'}{OD} = \frac{2.67}{4} = 0.67 \tag{3-14}$$

θ_{BCC} is never less than θ_{CCR} because the additional convexity constraint imposed by the BCC model makes its feasible region a subset of the CCR feasible region (Cooper et al., 2007). If a DMU is CCR efficient, it must therefore also be BCC efficient.

3.4 Properties and Extensions of the Basic Data Envelopment Analysis (DEA) Models

3.4.1 Scale Efficiency

From a DMU's CCR and BCC technical efficiency scores, one can determine its *scale efficiency* (Cooper et al., 2007):

$$\textit{Scale Efficiency} = \frac{\theta_{CCR}}{\theta_{BCC}} \tag{3-15}$$

This definition leads to the following breakdown of efficiency scores:

$$\theta_{CCR} = \theta_{BCC} \times \textit{Scale Efficiency} \tag{3-16}$$

Therefore, while the BCC model, with its VRS assumption, measures only pure technical efficiency, the CCR technical efficiency score consists of a combination of pure technical efficiency and scale efficiency. A BCC efficient DMU is scale efficient (with a scale efficiency score of 1) only if it is operating under constant returns-to-scale (u_0 = 0), its most productive scale size (Cooper et al., 2007). Returning to Figure 3-3, only DMU B, which is both CCR and BCC efficient, is scale efficient. DMU A, which is BCC efficient and therefore displays pure technical efficiency, is scale inefficient as it is operating under increasing returns-to-scale. That is, its marginal productivity is greater than its average productivity, meaning that an increase in its input will provide a proportionally greater increase in its output than if it were operating at its most productive scale size. Similarly, DMU G, which is also BCC efficient and therefore displays pure technical efficiency, is scale inefficient as it is operating under decreasing returns-to-scale. That is, its marginal productivity is less than its average productivity, meaning that an increase in its input will provide a proportionally smaller increase in its output than if it were operating at its most productive scale size. Such a decomposition of efficiency scores is useful in identifying the sources of inefficiency, be they inefficiency of operations (as illustrated by pure technical inefficiency) or inefficiency due to the scale of operations (as illustrated by scale inefficiency).

3.4.2 Units and Translation Invariance

Unit's invariance refers to the property that a DMU's efficiency score is independent of the units in which the inputs and outputs are measured, as long as the same units are used for each DMU. Both the CCR and BCC models are units invariant. Translation invariance refers to the ability to translate the inputs or outputs by some scalar value without altering the efficiency scores of the DMUs (Cooper et al., 2007). Figure 3.4 illustrates translation invariance under the VRS assumption.

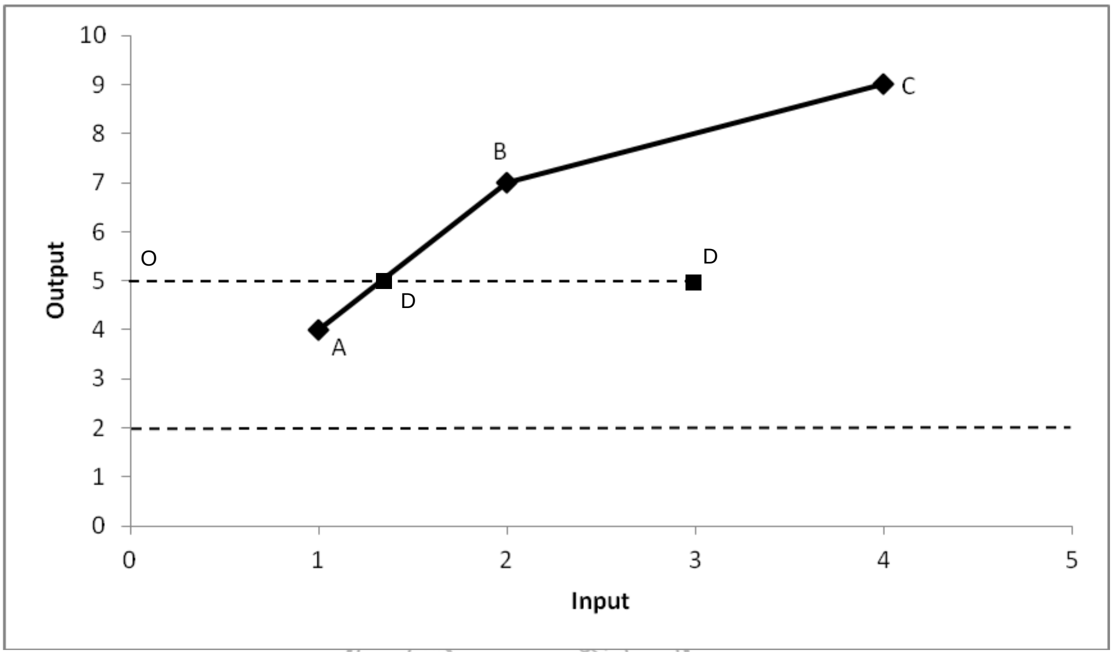

Figure 3-4 Translation invariance in data envelopment analysis (DEA)

It is evident that the efficiency score for DMU D, given by $\frac{OD'}{OD}$, is unaffected by translation of the output. If the output of all DMUs is decreased by two units (as illustrated by shifting the x-axis to the dotted line), D's efficiency score remains unchanged. Thus, an input-oriented BCC model is translation invariant in the outputs, whereas an output-oriented BCC model is translation invariant in the inputs.

Ali and Seiford (Ali and Seiford, 1990) have shown that the key to translation invariance lies in the convexity constraint and therefore the CCR model is not translation invariant. Translating the inputs or outputs by a scalar value will shift the CCR frontier in a manner that alters the efficiency scores, since the CRS frontier must pass through the origin. The translation invariance of the BCC model is a particularly useful property when handling negative values in the inputs or outputs, as it facilitates the elimination of the negatives via translation by the most negative value of that particular variable.

3.4.3 Restricted Multipliers

Although one of the major advantages of DEA is its use of variable rather than fixed weights, Dyson and Thanassoulis (1988) presented that such weight flexibility can result in some DMUs having all unfavorable inputs and outputs ignored in their assessment by assigning them zero multiplier values. To circumvent this problem, various restrictions can be applied to the input and/or output multipliers. One of the most popular methods of doing so is the assurance region method. This method constrains the relative magnitudes of the weights as follows:

$$L_{1,2} \leq \frac{v_2}{v_1} \leq U_{1,2} \tag{3-17}$$

$L_{1,2}$ and $U_{1,2}$ are the lower and upper limits that the ratio of the input multipliers (from the multiplier model) for inputs 1 and 2 can assume. Similar constraints can be placed on the output multipliers. The inclusion of such additional constraints in a DEA model will worsen the efficiency scores by restricting DEA's ability to select the most favorable multipliers for each DMU.

Great care must be taken in selecting lower and upper limits for the assurance region constraints as the ratio of the multipliers is likely to coincide with either limit. Since input multipliers can be interpreted as unit costs and output multipliers as unit prices, cost and price data are often used in setting the constraint limits. The assurance region method has the advantage of not requiring knowledge of actual costs and prices, data that is often not precisely available. Instead, only the relative costs and prices of the various inputs and outputs need to be known. Further, the use of lower and upper bounds allows for the accommodation of the different levels of costs and prices that may occur. In light of this, the lower limit of an assurance region constraint such as the one above might be set as the minimum observed cost ratio of inputs 1 and 2, while the upper limit might be set as the maximum observed cost ratio of inputs 1 and 2. For further details on restricted multiplier DEA models, the reader is referred to (Cooper et al., 2007).

3.4.4 Ratios in Data Envelopment Analysis (DEA)

Emrouznejad and Amin (2007) make a pointed out that it is a problematic to use standard DEA models when one or more of the input or output variables are in ratio form. An example of the problem will be represented in Figure 3-5 which in this figure will be shown a single input being used to produce two outputs.

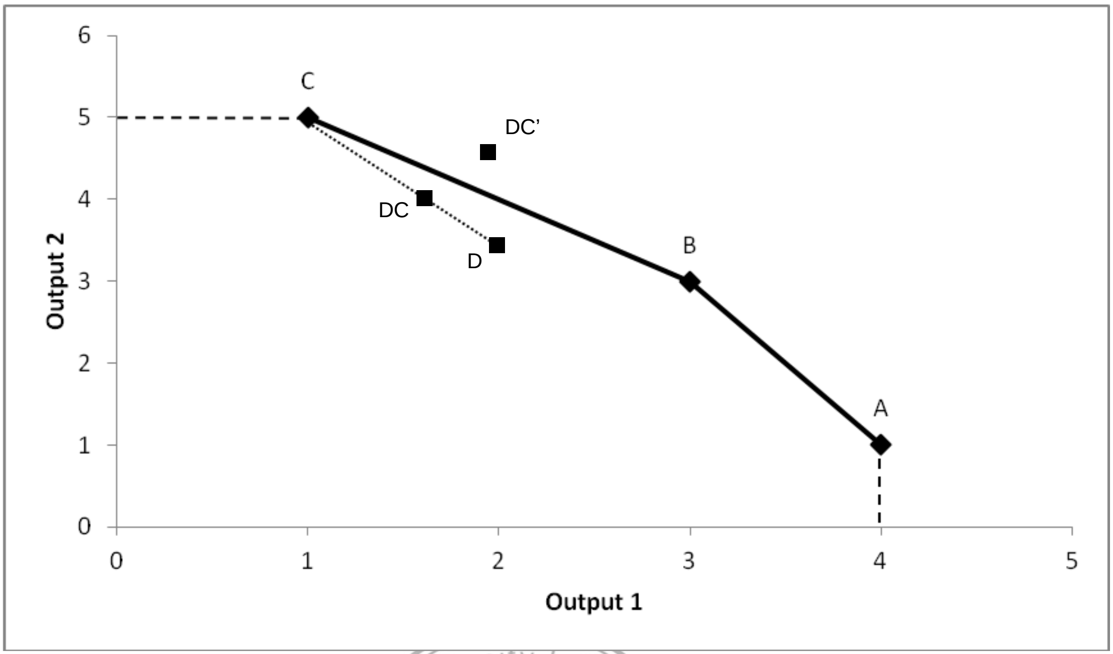

Figure 3-5 One output and two Inputs example illustrating the use of ratios in data envelopment analysis (DEA)

The efficient frontier consists of the three DMUs A, B and C. According to the convexity axiom of DEA, the convex combination of DMUs D and C, as represented by DMU DC, should also be a feasible DMU (fall within the feasible region). However, if output, for example, is in ratio form, the actual convex combination of DMUs D and C should be calculated as a weighted combination of the two DMUs which may fall outside the feasible region, as illustrated by DMU DC. Thus the convexity assumption of the BCC model may fail when one or more of the inputs or outputs are in ratio form, leading to incorrect efficiency scores. Hollingsworth and Smith (2003) have previously shown that the CCR model should not be used with ratio variables). Emrouznejad and Amin (2007) have developed a DEA formulation to rectify the problem of using ratios, however that is outside the scope of this work. For further details, the reader is referred to. Although the models presented in the subsequent chapters employ variables in ratio form, it will be shown that the presence of these ratios has little or no bearing on the model results.

3.4.5 Strengths and Weaknesses of Data Envelopment Analysis (DEA)

Data Envelopment Analysis has numerous strengths relative to other efficiency measurement techniques:

a. DEA can accommodate models with multiple inputs and multiple outputs, unlike techniques such as ratio analysis, which are limited to single input and single output efficiency measurements.

b. The units of the inputs and outputs in a DEA formulation need not be homogeneous.

c. Efficiency measurement techniques such as regression analysis result in the estimate of average relationships between variables, and these do not necessarily reflect efficient relationships. DEA, on the other hand, distinguishes between the units that are relatively more and less efficient and measures inefficiency compared with the efficient units in the set. Therefore, DEA measures efficiency relative to best practices rather than the mean or central tendency which incorporates both efficient and inefficient DMUs (Sherman, 1984).

d. DEA identifies the members of the efficient set used to evaluate each inefficient DMU.

e. Rather than using fixed weights applied to the inputs and outputs of all DMUs, DEA avoids making such a priori assumptions. Instead, it uses variable weights for each DMU in order to represent each DMU as efficiently as possible. DEA also does not require specifying a functional form relating the inputs to the outputs (Cooper et al., 2007).

Despite its strengths, DEA also has several limitations:

f. DEA is a comparative technique that measures relative and not absolute efficiency. Hence, DMUs that are deemed efficient by DEA are not necessarily absolutely efficient, but merely represent the "best of the bunch". It is quite probable that even "efficient" DMUs can improve their performance.

g. Unlike regression techniques, which are based on average performance, DEA is extremely sensitive to outliers that alter the shape of the efficient frontier. Therefore, measurement errors or other noise could seriously alter the efficiency scores.

h. While DEA directs attention to areas of inefficiency, it does not identify the specific factors that give rise to the inefficiency.

i. If the number of DMUs is very small, the efficiency discrimination of DEA becomes questionable, with a large portion of the DMUs being labeled as efficient. Charnes et al. (1989) developed the general rule of thumb that the number of DMUs should be at least three times the sum of the number of inputs and outputs. Cooper, Seiford and Tone (Cooper et al., 2007) extended the rule of thumb to include the requirement that the number of DMUs should also be at least the product of the number of inputs and outputs, as below:

$$n \geq \max \{3(m+s), m \times s\} \tag{3-18}$$

Once again, *n* represents the number of DMUs, *m* the number of inputs and *s* the number of outputs.

3.5 Limitations of Data Envelopment Analysis (DEA)

Like other techniques, DEA also has limitations. The first limitations of DEA, the results of DEA are dependent on the variables selected in the analysis (Charnes et al. 1989). It is like different combinations of input and output variables may change the DEA results. Also, the efficiency so will be abnormally large unless the sample size is large enough (Seiford and Thrall, 1990). Moreover, DEA may be sensitive to outliers, making the selection of DMUs critical. Outliers may greatly affect the shape of the efficient frontier and alter the efficiency estimates (Donthu and Yoo, 1998). In addition, the data set subject to DEA analysis should not include negative numbers. And the last, as with all mathematical programming calculations, DEA calculations can be affected by alternate optima, cycling, and degeneracy problem (Charnes et al, 1989).

3.6 Research Design

As illustration of Data Envelopment Analysis (DEA) application on organizational performance, we have selected a large retailing fashion brand industries which consisting of six international fashion brand industries. The first and the most crucial step is the selection of some common inputs and common outputs, those reflect to the analyst's interest. There are no restrictions in selection of inputs and outputs, but smaller input amounts and larger output amounts are preferable in this study. One of the basic features and also very important features of DEA methodology is that measurements units of the different inputs and outputs do not need to be congruent, which mean some inputs and outputs may involve number of persons, areas of floor space, unit of stores, etc.

Based on the literature review above, this study will develop a research framework which is drawn as Figure 3.6 below.

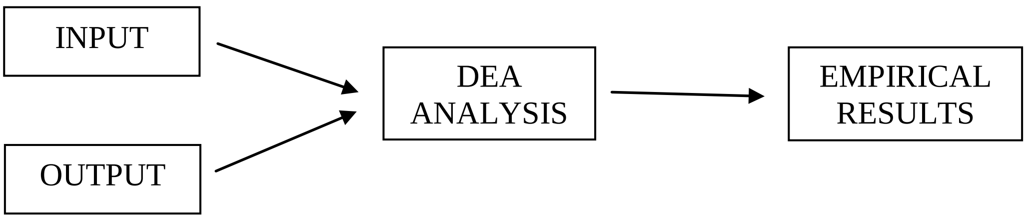

Figure 3-6 Research framework

3.7 Input and Output Selection

The right choice of adequate inputs and outputs is one of difficult steps in the DEA utilization. In this study there have 2 inputs and 2 outputs are choices as measures of operational efficiency for evaluating of six fashion brand samples.

1. Input :
    a. Total operating expense are total ongoing costs for running a product, business, or system, expect labor costs.
    b. Assets are anything tangible or intangible that is capable of being owned or controlled to produce value and that is held to have positive economic value.
2. Output :
    a. Net income is referred to as the net profit, it is computed as the residual of all revenue and gains over all expense and loss for the period time.
    b. Revenue is income that company receives from its normal business activities, usually from the sale of goods or services to customers.

CHAPTER FOUR
RESEARCH RESULTS

This chapter will present the decision making unit (DMU) whose chosen for this study, also this chapter will be present the descriptive analysis of the data collection, input and output from six international fashion brand company as the decision making unit (DMU). In this chapter will be discussing the result of the calculation data using Data Envelopment Analysis (DEA) method.

4.1 Decision Making Unit (DMU) Background

In the previously chapter mentioned data envelopment analysis system comparing the relative efficiency between each DMU, need to be able to compare with each other homogeneity between these units; higher homogeneity of the evaluated units, a measure of efficiency, the better, the higher the accuracy.

Every decision making unit below have similarly product input and product output which all of them are produce the luxury fashion goods and accessories. The decision making unit are listed below:

Table 4.1 Decision making unit (DMU) listed table

DMU	Year of Founded	Head Office	Product Output
Burberry	1856	London, England	Clothing, accessories, perfumes
Coach	1941	New York, United States	Handbag, watches, accessories, footwear, eyewear
Prada	1913	Milan, Italy	Clothing, accessories, cosmetics, jewelry, perfumes, wines, watches
Louis Vuitton	1854	Paris, France	Accessories, handbag, luxury goods
Ralph Lauren	1967	New York, United States	Clothing, footwear, fragrances, jewelry
Christian Dior	1946	Paris, France	Clothing, perfumes, cosmetics

4.2 Data Collection

The data selected in this study is from the financial statement of the six international fashion brand companies. The data are selected from 2012 annual statement and 2013 annual statement of each company, input variables as the total expense and assets, whereas output variables as net income and revenue, which considered among DEA model selected input and output variables are required to have.

The 2012 input and output table is shown as below:

Table 4.2 2012 Fashion brand company input and output table

DMU	Input		Output	
	Total Expense	Assets	Net Income	Revenue
Burberry	2,220,000,000	2,426,500,000	394,500,000	2,785,500,000
Coach	1,954,089,000	3,104,321,000	1,038,910,000	4,763,180,000
Prada	1,382,989,200	3,779,156,400	347,058,000	1,856,847,600
Louis Vuitton	26,618,400,000	59,997,600,000	4,108,800,000	33,723,600,000
Ralph Lauren	5,820,100,000	5,416,400,000	681,000,000	6,859,500,000
Christian Dior	25,862,400,000	62,674,800,000	1,418,400,000	32,374,800,000

Notes: units in US Dollars

Examine the data above, the Louis Vuitton and the Christian Dior is two of the higher input and output. Where Louis Vuitton using about US$ 59 billion of his assets and about US$ 26 billion for the total operation expense. And Christian Dior who spent US$ 25 billion to his total operation expense and they have about US$ 62 billion of assets. It is different with the other four companies which are using lower input to produce their output.

The 2013 input and output table is shown below:

Table 4.3 2013 Fashion brand company input and output table

DMU	Input		Output	
	Total Expense	Assets	Net Income	Revenue
Burberry	2,356,500,000	2,619,000,000	381,000,000	2,998,500,000
Coach	2,173,607,000	3,531,897,000	1,034,420,000	5,075,390,000
Prada	1,523,672,400	4,236,072,000	375,382,800	2,073,678,000
Louis Vuitton	27,753,600,000	66,808,800,000	4,123,200,000	34,978,800,000
Ralph Lauren	5,818,100,000	5,418,200,000	750,000,000	6,944,800,000
Christian Dior	28,549,200,000	66,734,400,000	1,717,200,000	35,857,200,000

Notes: units in US Dollars

From table 4.2 and table 4.3 some company makes increasing on input value it can be happened maybe because those companies add more value on assets or maybe they used more expense in their operational. But there have some company did not make increase on their output like Burberry Company. Burberry adds more input value both in Total Expense and Assets but their output still go down.

The company who used more input to gain output is not necessary in the efficient condition. And not necessary the company with the low input value and output value is the inefficient company. There are a lot of reason will be effect in the reliability were affect to the company performance, some of the reason it can be from the decision who decide by decision making unit itself. Perfect timing and perfect decision making will be taking the company to the highest level position on the fashion industry competition market.

Table 4.4 Summary statistics on input and output data variables table

Year		Total Expense	Assets	Net Income	Revenue
2012	**Maximum**	26,618,400,000	62,674,800,000	4,108,800,000	33,723,600,000
	Minimum	1,382,989,200	2,416,500,000	347,058,000	1,856,847,600
	Mean	10,642,996,367	22,898,129,567	1,331,444,667	13,727,237,933
	Std. Dev.	11,122,768,011	27,205,980,433	1,295,942,456	13,758,234,029
2013	**Maximum**	28,549,200,000	66,808,800,000	4,123,200,000	35,857,200,000
	Minimum	1,523,672,400	2,619,000,000	375,382,800	2,073,678,000
	Mean	11,362,446,567	24,891,394,833	1,396,867,133	14,654,728,000
	Std. Dev.	11,952,248,788	29,625,555,789	1,301,327,869	14,764,653,163

Notes: units in US Dollars

Table 4.4 gives summary statistics. It includes descriptive statistics pertaining to the outputs (total net income and revenue) and inputs (total operation expense and total assets) of the sample during the 2012 to 2013 period. As is shown, the fashion brand industry during 2012 to 2013, fashion brand company focused extensively on improving their quality of investment, which resulted in an 8% increase in the investment averages in the sample, from $22,898 billion to $24,891 million. In addition, the average amount of revenue over the sample period reflected almost the same high growth path of 6.8%, with $13,727 billion in 2012 compared to $14,654 billion at the end of 2013.

This study also used Pearson correlation coefficient to verify the results were highly positive correlation as shown in table 4.5 for year 2012 and table 4.6 for year 2013 below.

Table 4.5 2012 Pearson correlation input and output variables coefficient table

	Total Expense	Assets	Net Income	Revenue
Total Expense	1.000	0.993	0.790	0.998
Assets	0.993	1.000	0.764	0.993
Net Income	0.790	0.764	1.000	0.805
Revenue	0.998	0.993	0.805	1.000

Table 4.6 2013 Pearson correlation input and output variables coefficient table

	Total Expense	Assets	Net Income	Revenue
Total Expense	1.000	0.995	0.817	0.998
Assets	0.995	1.000	0.828	0.995
Net Income	0.817	0.828	1.000	0.827
Revenue	0.998	0.995	0.827	1.000

4.3 Data Calculation Using Data Envelopment Analysis (DEA)

The implementation of DEA on measuring efficiency can be divided in two ways, input oriented approach and output oriented approach. Basically, if the decision making unit (DMU) is easier to control the output side variable, they should be adopted output oriented model, otherwise if the decision making unit (DMU) more difficult to control their output variables, they should be adopted input oriented variables. In luxury fashion brand industry is easier to adjust the input side, The output side more difficult to control because some of famous fashion brand customer is more unique than the others industry. Some customer just loyal only to one brand and some of them also prefer to the segment class.

In this study, CCR and BCC model are used to calculate the technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency. This CCR and BCC model calculation below are using DEA-Solver, which used to know are the company is in efficiency or inefficient and to know which problem supposed to fix in order to improve their performance and make the better results in the next future.

The CCR-Input oriented calculation result is shown below:

Table 4.7 2012 CCR-input oriented fashion brand company rank and score table

DMU	Rank	Score
Coach	1	1.000
Ralph Lauren	2	0.825
Burberry	3	0.751
Prada	4	0.551
Louis Vuitton	5	0.520
Christian Dior	6	0.513

Table 4.8 2013 CCR-input oriented fashion brand company rank and score table

DMU	Rank	Score
Coach	1	1.000
Ralph Lauren	2	0.892
Burberry	3	0.797
Prada	4	0.583
Louis Vuitton	5	0.539
Christian Dior	6	0.537

Table 4.7 above is presented of CCR-Input rank and score for every company on year 2012, Coach, Inc. placed on the first position which marked with the score 1, whereas Christian Dior placed on the last position on that year with score 0.513. Table 4.8 for year 2013 also presented the same result of rank for each company but there have a little bit differentiation score of each company, it is mean every DMU sample has increasing in their performance.

The highest score on those two tables above means that company is the most efficiency than the other companies on that period, whereas the lowest score mean that company is the inefficiency company compares the other DMUs.

The BCC-Input oriented calculation is shown below:

Table 4.9 2012 BCC-input oriented fashion brand company rank and score table

DMU	Rank	Score
Ralph Lauren	1	1.000
Burberry	1	1.000
Coach	1	1.000
Prada	1	1.000
Louis Vuitton	1	1.000
Christian Dior	6	0.985

Table 4.10 2013 BCC-input oriented fashion brand company rank and score table

DMU	Rank	Score
Ralph Lauren	1	1.000
Burberry	1	1.000
Coach	1	1.000
Prada	1	1.000
Louis Vuitton	1	1.000
Christian Dior	1	1.000

Table 4.8 and Table 4.9 above presented about BCC-Input rank and score of each DMUs, where in 2012 all of the DMU is in efficiency position, except Christian Dior which in inefficient condition. Table 4.9 in year 2013 the BCC-I result shows that all of the company is in efficiency position.

4.4 Summary

In this study, DEA Solver software operation is performed, at first by using CCR-Input oriented model calculates technical efficiency (TE), and then use BCC-Input oriented model calculates pure technical efficiency (PTE), and finally by the technical efficiency (TE) divided by the pure technical efficiency (PTE), to obtain scale efficiency (SE), this calculation shown by table 4.11 and table 4.12 below.

Table 4.11 2012 DMU fashion brand company efficiency analysis table

DMU	CCR Model Technical Efficiency (TE)	BCC Model Pure Technical Efficiency (PTE)	Scale of Efficiency (SE) [TE / PTE]	Scale of Return	Reference	Rank
Coach	1.000	1.000	1.000	CRS	5	1
Ralph Lauren	0.825	1.000	0.825	DRS	1	2
Burberry	0.751	1.000	0.751	IRS	0	3
Prada	0.551	1.000	0.551	IRS	0	4
Louis Vuitton	0.520	1.000	0.520	DRS	0	6
Christian Dior	0.513	0.985	0,521	DRS	0	5
Mean	0.693	0.997	0.695			

Table 4.11 shown the fashion brand companies in 2012 average technical efficiency (TE) was 0.693 (69.3%), pure technical efficiency (PTE) was 0.997 (99.7%), and scale of efficiency (SE) was 0.695 (69.5%), respectively, are still displayed about 0.307 (30,7%), 0.003 (0.3%), and 0.305 (30.5%) space to improvement.

Table 4.12 below shown the fashion brand companies in 2012 average technical efficiency (TE) was 0.725 (72.5%), pure technical efficiency (PTE) was 1.000 (100%), and scale of efficiency (SE) was 0.725 (72.5%), from this calculation there are still displayed about 0.275 (27,5%) space to improvement for technical efficiency (TE) and 0.275 (27.5%) space to improvement for scale of efficiency (SE), but in 2013 the pure technical (PTE) shown the absolute value where already reach the 100% of PTE score, it is mean the pure technical efficiency (PTE) does not to do improvement anymore because it is already fully efficiency.

Table 4.12 2013 DMU fashion brand company efficiency analysis table

DMU	CCR Model Technical Efficiency (TE)	BCC Model Pure Technical Efficiency (PTE)	Scale of Efficiency (SE) [TE / PTE]	Scale of Return	Reference	Rank
Coach	1.000	1.000	1.000	CRS	5	1
Ralph Lauren	0.892	1.000	0.892	DRS	2	1
Burberry	0.797	1.000	0.797	IRS	1	1
Prada	0.583	1.000	0.583	IRS	0	1
Louis Vuitton	0.539	1.000	0.539	DRS	0	1
Christian Dior	0.537	1.000	0.537	DRS	0	1
Mean	0.725	1.000	0.725			

According to Norman and Barry (1991) the reference number of efficiency for measure can be divided into four efficiency DMU strength. The first, strong efficiency unit (The Robustly Efficient Units) is related to the composition of the DMU reference collection, the relative efficiency value of 1, second, the edge of efficiency unit (The Marginal Efficient Units), its relative efficiency value of 1, however the DMU did not appear in the other inefficient, DMU reference concentration, third, non-edge efficiency units (The Marginal Inefficient Units), its relative efficiency value 0.9 and 1, such DMU input or output items as long as slight adjustment it can be reached relatively efficiency level, fourth, significant non-efficient units (The Distinctly Inefficient Units) is DMU whose obviously inefficient units, its refers to DMU with the efficiency value less than 0.9 or the DMU has much more room for improvement.

Slack variable analysis is the difference between the variable resource usages by the assessment unit, or in other words can be interpreted with the difference between the distance of evaluated units and efficiency goal target, for the relatively inefficient units. By observing its efficiency gap between the front edge is useful to know how to improving its resources on specific direction and magnitude. When the difference gap between the evaluated input and output variable units is 0, it means that input and output variables units already relatively efficient, also the use of resources has reached the optimum conditions, and does not need to adjust the inputs and outputs configuration items anymore, and if there is more than one entry input or output variable units is not 0, it means that input and output variable units is less than the relative efficiency (inefficiency) and the resources conditions are not optimal usage.

Table 4.13 2012 Slack variable analysis table

DMU	Score	Excess Expense S-(1)	Excess Assets S-(2)	Shortage Net Income S+(1)	Shortage Revenue S+(2)
Coach	1.000	-	-	-	-
Ralph Lauren	0.825	1,989,663,771	-	815,143,993	
Burberry	0.751	525,032,685	-	213,052,896	-
Prada	0.551	-	871,442,898	57,944,023	-
Louis Vuitton	0.520	-	9,205,320,645	3,246,745,093	-
Christian Dior	0.513	-	11,087,135,654	5,642,952,697	-

Table 4.13 above can be explain that some brand companies need to do more adjustment, both in input and output factors in order to maximize their efficiency, some input should be decrease and some output need to increase to reached the optimum condition. According to table 4.13, Ralph Lauren and Burberry Companies should reduce their expenses, respectively by 1,989 million and 525 million, also they need to increase the net income, respectively by 815 million and 213 million, whereas Prada, Louis Vuitton, and Christian Dior should reduce their assets, respectively by 871 million, 9,205 million, and 11,087 million, also they need to increase their net income, respectively by 57 million, 3,246 million, and 5,642 million to reach the efficiency target. But this condition does not to applied in Coach because this company already in optimum condition or in other words this company already in efficiency condition and just need to maintain this condition in future.

Table 4.14 below also showed the similarly results with table 4.13 which there has five companies need to do some adjustment in their input and output factors, two of them need to adjusted their expense and three of them need to adjust their assets, also they need to increase their net income to reach the efficiency condition. And from those two tables also showed the same results in Coach were this company still in efficiency condition and keep maintain their condition from 2012 to 2103.

Table 4.14 2013 Slack variable analysis table

DMU	Score	Excess Expense S-(1)	Excess Assets S-(2)	Shortage Net Income S+(1)	Shortage Revenue S+(2)
Coach	1.000	-	-	-	-
Ralph Lauren	0.892	2,215,279,822	-	665,426,206	
Burberry	0.797	593,327,220	-	230,127,099	-
Prada	0.583	-	1,025,975,093	47,255,459	-
Louis Vuitton	0.539	-	11,719,140,495	3,005,862,061	-
Christian Dior	0.537	-	10,943,260,251	5,590,889,590	-

From table 4.15 below can be describe the same results for the two period years just only 1 company placed in strong efficiency, but the other five companies are inefficient as table 4.13 and table 4.14 showed before, those five companies still need more adjustment their usage resources and create more output to make their performance better.

Table 4.15 2012-2013 Fashion brand company efficiency intensity classification

Year	Strong Efficiency	Edge Efficiency	Edge Inefficiency	Apparent Inefficiency
2012	Coach	–	–	Ralph Lauren, Burberry, Prada, Louis Vuitton, Christian Dior
2013	Coach	–	–	Ralph Lauren, Burberry, Prada, Louis Vuitton, Christian Dior

CHAPTER FIVE
CONCLUSION AND SUGGESTION

This chapter will be presents the major connotations of the conclusion of this study. The results are discussed and implications are suggested for wellness fashion industry literature. This study framework is used to know the efficiency performance of fashion brand companies and after they know their efficiency performances it can be uses to increasing their performance more in the future.

5.1 Conclusion

In the past recent times fashion trend and style became an important thing for some societies in this world. A wide variety of trend lifestyles and models are shown by several fashion brands, both local brands and world-class famous brands. In the very tight competition, makes every fashion house trying hard to increase their sales turnover and reached much more profit that they can reached. The efficiency and effectiveness are can be considered as important factors that contributing to the company as well as in improving and gaining maximum profits for each fashion brand company.

In this study that have been choses six world-class famous fashion brands companies as the samples of this research, they are Burberry, Coach, Prada, Louis Vuitton, Ralph Lauren, and Christian Dior, whose all of the world class famous fashion brand are produced the similar goods in fashion industry, like clothing, leather goods, accessories, perfumes and fragrances, watches, even the cosmetics.

Data Envelopment Analysis (DEA) is used in this study to calculate the efficiency of six famous fashion brands above. Two period times are used in this research study, which in 2012 and 2013. Analysis revealed that the two inputs and two outputs are selected for this study to fulfill the Data Envelopment Analysis (DEA) criteria analysis, total expense and assets as the inputs, net income and revenue as the outputs. This also supported the assumed correlations between Data Envelopment Analysis (DEA) inputs and outputs.

Data Envelopment Analysis (DEA) results showed that in 2012 mean score of CCR model efficiency was 0.693 with a standard deviation of 0.181, whereas the mean score of BCC model were 0.997 with a standard deviation of 0.005, in 2013 mean score of CCR model efficiency was 0.725 with a standard deviation of 0.182, whereas the mean score of BCC model were 1 with a standard deviation of 0. The mean efficiency score for the BBC model was slightly higher than the score for the CCR model.

From the results of this study found that in 2012 and 2013 only one company that is able to maximized their performance to generate the inputs become the outputs and make that company to be maximum efficiency, the company who has can be the best efficiency company in this study is Coach, Inc. While five other fashion brand companies are still in inefficient condition. Large amount of inputs and outputs does not guarantee the company has a good efficiency in their performance, this condition already showed by the Louis Vuitton and Christian Dior, whose two of them are contributed the biggest amount of inputs and also make produced the biggest amount of outputs, but within this study showed those two companies are in the last and two-last of the performance efficiency fashion brand companies ranking.

Redundant assets in a company does not guarantee that the company will get a lot of revenue, for example, the number of counter stores which will also lead to excessive operating expenses, both in terms of place investment, labor costs, and operating costs, the amount of assets that are used must be proportional to the degree of revenue and income can be earn by each company, but this problem is not easy to achieve, especially for fashion industry segment which in this study is focused on world-class fashion brand companies. In this case can be interpreted as not all counters will be able to earn the same level of revenue and income, also not all of counter stores are able to achieve the maximum target. It is depends on every counter stores to manage their performance and push-up their selling to the customers. In order to improve the quality of efficiency, besides reducing the usage of input factors should also be followed by improve the output factors that can be generated by the company.

5.2 Limitation and Suggestion for Future Research

This research study is only focus on international fashion brand industries with the similar product outputs, data collection are collected from each DMU company's financial statement with some adjustment in currency, which US Dollars is used as the currency for the calculation.

Additionally, there are some suggestions for education field and fashion companies, as follows:

a. Education field

This research found that the number of DMU have a big influence in accuracy of the result, number of DMU need to be larger, or insufficient data used on research will give much influence of the result accuracy. Data Envelopment Analysis (DEA) does not guarantee the cause or remedy for the identified inefficiency. Internal audits or peer review are needed to define the types task to finish them in the future research.

b. Fashion Brand Companies

In the international high-end class or luxury segment fashion brand industry, the amount of assets that are not the most important factor in terms of efficiency of the company, the big amount of assets also will influence the operational expense which used by the company, this condition if not comparable with the income amount, it will make the performance of the company to be inefficient. In this research through the Data Envelopment Analysis (DEA) methods, was found that several fashion companies are advised to trim the amount of assets they have, and some of it is advised to cut their operational expense. Increasing net income is also recommended in order to improve the quality of corporate efficiency, the latest trend and model on every session has a very large effect in this world fashion competition, quality control of products and after sales services also support the improvement of company brand image among the segment of luxury fashion brand lovers.

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