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Efficiency comparison of multiple brands within the same franchise: Data envelopment analysis approach

Eugene Y. Roh [a,*], Kyuwan Choi [b]

[a] Department of Marketing and Hospitality Service Administration, College of Business, Central Michigan University, Mount Pleasant, MI 48859, United States
[b] College of Hotel and Tourism Management, Kyung Hee University, Republic of Korea

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ABSTRACT

As the restaurant franchising industry increasingly diversifies its brands, it is pivotal for a firm to accurately assess the efficiency of brands within its franchise system. This research compares and contrasts the efficiency of different brands belonging to the same franchisor using data envelopment analysis (DEA). The sample was drawn from three brands that are in operation under the same restaurant franchisor. The results of the study showed that the efficiency of each establishment, as well as the brands, differed significantly from each other.

Managerial and strategic implications for franchisors and directions for future research are discussed.

1. Introduction

The role of the brand is an integral part of a firm's marketing strategy and is increasingly seen as a valuable asset and a source of differentiation (Lim and O'Cass, 2001; O'Cass and Grace, 2003). Aaker (1991) suggested that brand equity contributed to a firm's value through increased loyalty, awareness, and perceived quality. As such, strong brands deliver greater returns to shareholders with less risk (Madden et al., 2006). From a consumer's point of view, a brand identifies the source of the product and provides a promise or bond with the producer (Lassar et al., 1995).

Brand names in the service industry are particularly important for members of a franchised system because they can obtain systematic economies and market impact that could not be achieved through individual action (Bucklin, 1971). When a franchise possesses a robust brand, it enables the franchisor to create entry barriers to competitors and thus creates a competitive advantage by prohibiting duplication of image and product.

While some service firms only possess a single brand, it is interesting to observe that a substantial number of service firms offer multiple brands to communicate to a wide range of customers and diversify their markets. A broad line of products enables a firm to create more business opportunities for a sales force and channel partners (Best, 2004). For instance, Darden Restaurants Inc., the largest casual dining restaurant company in the world, owns and operates more than 1400 units with many different brands such as Red Lobster, Olive Garden, Bahama Breeze, and Smokey Bones Barbeque and Grill.

Aaker and Jacobson (2001) argued that measuring brand performance has become a crucial management task. While a number of researchers have attempted to measure the efficiency of brands, the existing approaches have exclusively centered on measuring the increased financial returns that the brand generates (Ambler et al., 2002; Schultz, 2004). In other words, universal brand valuation stresses a short-term incremental financial return rather than emphasizing efficiency. As such, Schultz (2004) argued that most of the valuation methodologies designed to measure product brands simply do not work in the corporate brand arena.

In a service organization, it is a challenge to accurately assess brand efficiency for a variety of reasons. The intangible nature of a service makes it difficult to objectively define and measure the service outputs being provided (Fitzgerald and Fitzsimmons, 1997). Nevertheless, ratios for output per unit of labor (labor productivity) and output per capital (capital productivity) are the two most frequently used single-factor approaches in measuring the productivity in the service industry (Brown and Dev, 1999).

Unlike traditional methods, DEA is a powerful tool that overcomes the limitations of conventional techniques to measure brand efficiency. Donthu et al. (2005) asserted that DEA is a better approach to measuring efficiency as the technique provides the diagnostic tool necessary for effecting productivity-based performance improvement. DEA can measure efficiency at the individual franchised unit level by simultaneously incorporating multiple inputs and outputs. The technique allows identification of the most efficient units which can then be used as a benchmark. An efficiency score is calculated for each unit relative to the best performer. As a result, over the past decade, DEA has been applied

* Corresponding author.
E-mail addresses: roh1y@cmich.edu (E.Y. Roh), kwchoi@khu.ac.kr (K. Choi).

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within a wide range of business disciplines for the selection of benchmarking partners (Keh et al., 2006).

Despite the importance of measuring productivity for service organizations, it is surprising that there has been relatively little empirical research on this topic (Johnston and Jones, 2004). Compared to the manufacturing industry, the practical use and academic study of DEA remains relatively limited in service industries. However, the area has attracted increased attention in recent years. There are a growing number of recent studies that measure productivity in the service and hospitality disciplines.

The service industry, particularly a franchisor with multiple brands, provides an ideal opportunity to illustrate DEA for the purpose of internal benchmarking. Specifically, a restaurant franchise was chosen to serve the purpose of this research because it offers a wide variation in competition, location, and neighborhood characteristics. Nevertheless, each franchise unit within a brand still adopts very similar menu concepts, standardized operating procedures, décor/design, production functions and technology.

The purpose of this paper is to empirically compare and contrast the efficiency of multiple brands within the same franchise utilizing DEA. The next section briefly reviews the literature on two different DEA models. Section 3 presents the research methodology. Section 4 discusses the empirical analysis and presents how managers can adopt the outcome of DEA operationally in the individual restaurant units. The final section concludes with managerial implications and suggestions for future research.

2. Efficiency measure and data envelopment analysis

Efficiency has been broadly defined as the maximum output from a given set of inputs assuming that all inputs and outputs were accurately measured (Farrell, 1957).

Johnston and Jones (2004) argued that measuring efficiency within the service industry presents a number of obstacles since the conventional approaches were derived largely from manufacturing. They indicated that in a service industry the customer is personally involved in the process of delivery and as a result efficiency is not solely derived from the service provider's actions. Additionally, the distinct characteristics of services such as intangibility and heterogeneity can cause customers to place as high a degree of importance on the psychological outcome of the service experience as they do on the actual output.

Historically, service industries have utilized ratio analysis (Baker and Riley, 1994), and break-even analysis for appraising the effectiveness of tourism management (Wijeysinghe, 1993), and yield management for analyzing the efficiency of hotels (Brotherton and Mooney, 1992; Donaghy et al., 1995). While labor productivity and partial-factor statistics (i.e., revenue per available seat hour) are prevailing measures of efficiency, these methods have major drawbacks. For instance, labor cost percentage does not fully explain labor utilization because it fails to consider advancement in technologies, changes in the facility and other labor related costs such as benefits and incentives. Thus, measuring efficiency through labor productivity is not an effective measurement in the dynamic heterogeneous environments (Taylor et al., 2009). Also, partial-factor statistics have limited utility and frequently do not satisfactorily explain the nature of operational efficiency. For this reason, traditional efficiency measures have become the subject of extensive criticism from marketing research because they are confined by the limited number of operational characteristics used to predict efficiency (Donthu et al., 2005).

In sum, attempts to operationalize efficiency using these traditional measures have created confusion, inconsistency and even controversy, with the corresponding measures utilized running the gamut from physical value (e.g. asset turnover ratio) to monetary value (e.g. revenue/number of employees). Previous research on efficiency has also been limited by its failure to show that the productivity of individual units within a system should be evaluated relative to other units within that system.

Donthu et al. (2005) advocated the need for a more rigorous methodological approach in order to develop a ratio system that can handle multiple inputs and outputs simultaneously. Ideally, such a system would measure relative to best productivity or efficiency as opposed to absolute or relative to average values. Thus, this innovative technique would substantially mitigate shortcomings associated with traditional measurement techniques.

DEA is a mathematical programming model proposed by Charnes et al. (1978) that provides an objective method to structure various measures into a single, meaningful performance score (CCR Model). Later the model was improved by Banker et al. (1984) (BCC model). Currently, DEA has become an increasingly popular diagnostic management device and is widely used in many business disciplines such as operations research and production (Lozano et al., 2004; Keh et al., 2006), retail stores (Donthu and Yoo, 1998), advertising (Luo and Donthu, 2001), performance appraisals of salespersons (Boles et al., 1995), insurance companies (DePree et al., 1995), and non-profit service providers (Borja and Triantis, 2007; Ahn et al., 1988). The model has even been extended to the evaluation of service industries (Morey and Dittman, 1995; Hwang and Chang, 2003; Wober and Fesenmaier, 2004; Reynolds and Thomson, 2007).

Mathematically, DEA is the ratio of the weighted sum of outputs to the weighted sum of inputs. DEA can be used to separate efficient units from inefficient units based on whether or not the subject units lie on the efficient frontier. The efficient frontier is a series of points connecting the most productive units given input and output combinations in the analysis. This procedure is similar to selecting units with the highest slope at any given input under consideration. At the individual establishment level, DEA provides a rich diagnostic tool through sensitivity analysis which helps the inefficient outlet identify how to allocate resources more efficiently and improve its productivity (Donthu and Yoo, 1998).

2.1. DEA techniques: CCR model and BCC model

In DEA, optimal decision-making units (DMUs) are derived from a group of DMUs and a relative efficiency is calculated by comparing optimal DMUs with non-optimal, or inefficient, DMUs. The researchers denote DMUs by subscript $j = \{1, 2, \ldots, n\}$, inputs by $i = \{1, 2, \ldots, m\}$, and outputs by $r = \{1, 2, \ldots, s\}$. For a given DMU j, let x_{ij} be the amount of input i used and y_{rj} the amount of output r produced. Only the case of $x_{ij} \geq 0$, $y_{rj} \geq 0$ is considered.

Mathematically, in the input-oriented CCR model, the efficiency value of a particular DMU o is calculated as follows. Let θ_o^* be the efficiency score for the DMU o. Then,

$$\theta_o^* = \min \theta_o$$

subject to

$$\begin{aligned} &\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta_o x_{io} && i = 1, 2, \ldots, m \\ &\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} && r = 1, 2, \ldots, s \\ &\lambda_j \geq 0 && j = 1, 2, \ldots, n \end{aligned} \tag{1}$$

where m = number of inputs; s = number of outputs; n = number of DMUs; x_{ij} = amount of input i used by DMU j; x_{io} = amount