Benchmarking of Advertising Efficiency in U.S. Car Market Using Data Envelopment Analysis

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Abstract

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Measuring advertising efficiency is an important and challenging issue in marketing. It is important since advertising spending consumes the biggest part of a marketing budget. Yet many firms have difficulty to determine the optimal level of advertising budget and to allocate this budget across different media. And it is challenging since finding a methodology that can incorporate multiple effects of advertising (cognitive, affective and behavioral), measure efficiency in a competitive setting, and provide guidelines for advertising improvement is difficult. This thesis explores the usability of an alternative method, data envelopment analysis, in measuring advertising efficiency. The focus of this research, which comprises of two studies, is to benchmark advertising efficiency of major car-models in U.S. car market with application of DEA. The objective of first study is to measure the level of over-advertising at macro level, in the whole industry, and also to determine the level of advertising inefficiency in each major media. The objective of second study is to measure advertising inefficiency of each car-model in creating different levels of advertising effects, and also to investigate the influence of strategy on advertising effects and efficiency.

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At the end, I would like to proffer this dissertation to my deceased grandparents Jalal Vaseghi, Majid Moshirian, Hormat Zia, and my lovely grandmother Nahid.

Table of Contents

List of Figurers

List of Tables

List of Equations

Introduction

Advertising budgeting is an important issue since the biggest part of a marketing budget is usually spent on advertising and promotion (Ambler, 2000). Generally, firms are interested in finding out whether they are overspending or under-spending on advertising (Kotler & Keller, 2012), as too little spending may lead to a failure of even the most brilliant campaign, while too much spending results in a waste of money, regardless of the campaign's success (Sissors & Bumba, 1996). Many empirical studies suggested that advertising has a positive long-term impact on differentiation, brand equity and sales (Boulding et al., 1994; Jedidi et al., 1999; Berkowitz et al., 2001; Ehrenberg et al., 2002). However, we need to distinguish between advertising efficiency and advertising effectiveness. While advertising effectiveness investigates the influence of advertising practices on those end-objective variables, advertising efficiency explores financial justification of advertising by measuring the ratio of advertising outputs over advertising expenditure. Many firms have difficulty in defining the optimal level of advertising expenditure and many scholars believe companies tend to over-advertise (Bass, 1979; Aaker & Carman, 1982; Bhargava et al., 1994; Miller & Cioffi, 2004). In advertising investment, there is always a turning point, above which there is diminishing marginal return. As a firm continues to increase its advertising budget it reaches a point above which additional gains as a result of the incremental expenditures is not worthwhile (Kim & Cheong, 2009). However, finding this optimal point is not always easy, and many firms tend to increase advertising budgets regardless of this issue. Overall, practitioners would like to find out whether they are using their advertising budget efficiently, what the optimal level of advertising budget is, and how best it should be allocated among various media. Accordingly, as indicated by Luo and Donthu (2001), there is a high demand for measuring advertising efficiency.

Researchers face at least four challenges in analyzing advertising efficiency. Firstly, advertising effects are not one-dimensional. Based on literature, advertising has three levels of cognitive, affective and behavioral effects. The first goal of advertising is to build awareness among unaware audiences and then provide them with knowledge about the product or brand (cognitive stage). At the second stage, it has to create a form of liking and preference among audiences and lead them toward purchase intention (affective stage). Finally, the ultimate goal of advertising is to increase purchase intent, sales and/or profit (behavioral stage). All these effects are important and should be considered simultaneously in measuring advertising efficiency. However, because complete information is not always available for empirical researches, advertising practitioners and scholars are limited to focus either on one or some of these effects (e.g. Luo & Donthu, 2001; 2005; Färe et al., 2004; Büschken, 2007; Pergelova et al., 2010).

The second challenge is handling multiple inputs and outputs at once. Not only measuring the different effects of advertising is troublesome, but also finding a methodology that can incorporate all those outputs at the same time, is challenging. Not all methods allow having more than one output variables at a time. The relationship between different effects of advertising is a complex one. All these effects are correlated, while there is no consent regarding the causal path between them. Furthermore, the relationships between advertising expenditure and each of those outputs are not well explained and clear yet.

The third challenge is measuring efficiency in a competitive context. Not all methods take competition dimension into consideration. Advertising is not taking place in vacuum setting. Firms make their advertising decisions in a competitive context, influencing and taking influence from other firms' decisions. At the same time, consumer decisions are resulted by competition at each stage of ad and brand information processing (Laroche et al., 1996; Teng & Laroche, 2007). Accordingly, competition is an important dimension of advertising researches and should be incorporated in the applied methodology.

The fourth challenge is that a good methodology, not only should be able to measure the overall relative efficiency in a competitive setting, but also should provide each firm with some insight regarding how to modify and/or reallocate its advertising budget across different media, for best favorable results and improved efficiency. As indicated by Kim and Cheong (2009), the importance of using scientific research rather than industry rules of thumb has been well recognized in theory and practice.

This thesis suggests Data Envelopment Analysis (DEA) as an appropriate methodology for measuring advertising efficiency. In this research I focused on advertising practices in U.S. automobile industry. To overcome the first challenge, best effort has been made to analyze advertising efficiency with consideration of all effects of advertising through purchase process. To do so, I gathered a comprehensive dataset of U.S. car market, composed of advertising expenditures information in different media, and outcomes at different stages of purchase funnel (cognitive, affective and behavioral). Thereafter, DEA is utilized to analyze and evaluate advertising efficiency of car-models. DEA is a frontier analysis that can overcome the remaining challenges. As a non-parametric approach, DEA does not require the imposition of functional relationship between dependent and independent variables and can handle multiple input and outputs at the same time. It overcomes the third challenge by measuring advertising efficiency in a competitive setting. DEA is a frontier benchmarking method and thus estimates the efficiency of each unit relative to the efficiency of best-practices that assumed to be located at the frontier envelope. Finally, DEA conquer the fourth challenge by providing the results of peer analysis and slack analysis. For each inefficient car-model, it determines a linear combination of best-practices in the industry as role models to emulate (peer analysis), and also determines the level of excess (and shortfalls) in each input (and output) to be adjusted (slack analysis). DEA first developed in 1978 by Charnes, Cooper and Rhodes, based on Farrell's (1957) ideas of efficiency. Since then, there has been a rapid growth in this field, and DEA has been used extensively in operation research, economics and management. A bibliography of DEA by Emrouznejad et al. (2008) has mentioned more than 4000 research articles published in journals and book chapters. This number would have exceeded 7000 publications by inclusion of dissertation, working/research manuscript and conference papers. They also identified more than 2500 distinct authors in the field in the period of 1978-2007. Although Charnes et al. (1985) suggested applying DEA to analyze efficiency of marketing efforts long ago, it adopted in marketing literature quite recently.

The main objective of this thesis is to explore the usability of an alternative method, data envelopment analysis, in measuring advertising efficiency. This research aims to benchmark advertising efficiency of major car-models in U.S. automobile industry and is composed of two empirical studies with application of DEA. In the first study, I used DEA to measure the level of over-advertising at macro level, in the whole industry. I also investigate the level of advertising inefficiency in each major media within this industry. In the second study, I strived for more benchmarking details, identification of best-practices in the market, and guidelines for advertising improvement of inefficient car-models. The second objective of this study was to investigate the influence of strategy on advertising effects and efficiency. Overall, this thesis contributes to the literature in following respects.

To my best knowledge, this is the most comprehensive research study on advertising efficiency with application of DEA. Almost none of the studies in advertising budgeting considered all effects of advertising in their analysis. While one group of researches focused on behavioral stage and included sale as the single output of advertising (e.g. Luo & Donthu, 2001; 2005; Färe et al., 2004; Pergelova et al., 2010), the other groups only took communicational effects of advertising into their consideration (e.g. Büschken, 2007; 2009). Even Kim and Cheong (2009), who indicated that ideal output variables should be a combination of multiple sales and communication variables, only included revenue and brand-value in their study. For this research, I went further by looking at the whole purchase funnel and inclusion of awareness, attitude, purchase intention and sales volume as output variables. Additionally, in this research I tried to take as much as possible media into consideration. I included eighteen different media, categorized into five classes of broadcast, print, outdoor, internet and B2B, as input variables.

Moreover, unlike most of advertising studies on car industry (e.g. Greuner et al., 2000; Büschken, 2007; 2009, Jackson, 2010) that focus on efficiency of advertising at brand-level (e.g. BMW versus Toyota), this paper concentrates on those effects at model-level (e.g. 3series versus Camry). In real world, especially for automobile brands that produce a wide range of car-models, it is quite unrealistic and simplistic to assume that efficiency of advertising for all car-models under the umbrella of that brand is the same. Moreover, since most of the advertisements in car models are model-specific, it gives more ecological validity to run the analysis at product-level. Finally, the results would be more practical as it provides guidelines for media planning of each specific car-model rather than an average strategy for all models under the same brand-name.

Furthermore, in this thesis I tried to focus at both input and output-side of advertising efficiency to provide more comprehensive results and implications in both media planning and advertising effects literature. In study 1, input-oriented method of DEA was utilized with the objective of minimizing advertising budgets and modification of media shares. However, in study 2, I applied output-oriented method of DEA, with the objective of increasing advertising outputs with the given level of advertising budget.

Finally, in study 2 of this research, I investigated the influence of strategy on advertising effects and efficiency. I was interested to identify plausible differences between Porter's major strategies, differentiation and cost-leadership, in advertising context. These results reveal the strengths and weaknesses of dominant strategies in each category of effects (cognitive, affective and behavioral) and level of advertising inefficiency in producing each of them. This can help managers in advertising decision making process, to apply appropriate techniques and strategies to mitigate their weaknesses. It is also beneficial for companies with wide range of car-models with different strategies to manage advertising practices of each car-model accordingly.

The rest of this thesis is organized in the following manner. In the literature review section, a brief overview of benchmarking process, advertising effects and strategic group analysis is presented. In review of benchmarking, frontier approach and differences between existing quantitative methods are explained. Application of DEA is justified by emphasizing on its advantages and its fitness for this specific research. Advertising effects are briefly reviewed for better selection of output variables in both study 1 and study 2. Since the objective of study 2 is to investigate the influence of strategy on advertising effects and efficiency, a concise literature review of strategic group analysis is provided as well. In the next chapter I introduce the models. After an introduction of DEA, chosen methods used in study 1 and study 2 are explained more in details. This section ends with presentation of hypotheses. In the methodology section, after a brief description of data, the research procedure in each study is discussed. This section is followed by presentation of results and findings. I conclude this manuscript with emphasizing on theoretical and managerial implications, major limitations of this research and direction for future researches.

Literature Review

Benchmarking

Benchmarking is a quite recent established tool that has drawn wide attention of scholars and practitioners in various disciplines (Anand & Kodali, 2008; Fong et al., 1998). The concept developed in the late 1970s in Xerox Corporation, defined as the search for industry best practices that will lead to superior performance (Camp, 1989). Based on modern terminology, benchmarking is the systematic comparison of one's business process and performance metrics against industry best practices. Bogetoft et al., (2011) defined benchmarking as relative performance evaluation of firms (or other production entities) that transforms the same types of inputs (resources) into the same type of outputs.

Different Methods of Benchmarking

In modern benchmarking, frontier analysis methods are most common. The purpose of frontier analysis is to distinguish the optimal efficient decision making units, which assumed to be located at the frontier, from the inefficient ones that are located below the frontier (Thore, 2002). In overview of quantitative benchmarking methods, we should distinguish between parametric and non-parametric methods and also between stochastic and deterministic methods (Bogetoft et al., 2011). The difference between parametric and non-parametric methods is that in the former, the model structure is specified a priori while in the latter it is determined from data instead. Simply put, in non-parametric approach the number and nature of the parameters are flexible and not fixed in advance. There is also a distinction between deterministic and stochastic methods. Stochastic methods allow individual observations to be affected by random noise, and try to identify the underlying mean structure stripped from the impact of the random elements. In deterministic methods however, randomness is not recognized, and any variation in data is considered to contain significant information (Bogetoft et al., 2011). Among frontier methods data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are the two methodologies that are most widely recognized, extensively used in the literature, and rapidly growing in theory and practice (see the bibliography of DEA by Emrouznejad et al. (2008) and literature review of SFA by Kumbhakar & Lovell (2000) for further detail). DEA is a non-parametric, deterministic approach, while SFA is a parametric, stochastic method. Each of these two approaches has its own pros and cons, which are well stressed in the literature (Charnes et al., 1994; Luo & Donthu, 2005). SFA as a parametric approach calculates estimates of efficiencies of each decision making unit (observation) based on a hypothesized function. Based on all observations SFA produces an efficient frontier line that encompasses the best performers, and thus a single optimized regression equation is assumed to apply to all decision making units. Moreover, as a stochastic method, SFA is able to separate random noise from inefficiency (Charnes et al., 1994). On the other hand, DEA as a non-parametric approach is a linear programming formulation that defines a nonparametric relationship between multiple outputs and multiple inputs by building an efficiency frontier. Moreover, DEA as a deterministic approach incorporates noise as part of the efficiency score. One major difference between two methods is that SFA focuses on all observations and form the efficient frontier based on a single-optimization statistical approach, while DEA focuses on individual observations, and forms the efficient frontier after N optimizations, one for each observation (Charnes et al., 1994). Moreover, unlike SFA, DEA does not require the imposition of specific functional form relating the independent variables to the dependent variable, and also specific assumption about the distribution of the error terms (e.g. independently and identically normally distributed) (Charners et al., 1994) and accordingly, is very applicable in cases with complex and/or unknown nature of relationship between inputs and outputs (Zhu, 2003). Finally, DEA can easily deal with multiple outputs at the same time; it provides not only the efficiency scores, but also the slack results, which reveals the excess usage (or shortfalls) of each input (or output), in each decision making unit. Overall, while SFA is advantageous by allowing a better separation of noise and inefficiency, DEA is advantageous by having a very flexible production structure (Bogetoft et al., 2011) and has been identified as the manager-preferred method in analysis of efficiency (Luo & Donthu, 2005).

Advertising Benchmarking

Advertising benchmarking is the process of comparing one's advertising efficiency to the industry best practices. Based on literature (Donthu et al., 2005; Kim & Cheong, 2009) it is composed of three main steps: (1) relative measurement of advertising efficiency (2) setting a reference set of role models for inefficient firms (3) and strategic adjustment and/or reallocation of advertising budgets. In the first step a methodology should be applied to measure relative advertising efficiency to identify overall best performers that operate efficiently in advertising spending within the industry. Then, in the second step, each inefficient firm should set its advertising goals and identify a reference set of best practices to emulate accordingly. Finally, at the third step, based on advertising goals and chosen role models, firm should strategically adjust and/or reallocate advertising budget of each medium, to become as efficient as its reference. In this thesis I suggested DEA as the preferred methodology for advertising benchmarking for different reasons. First, I wanted to measure advertising efficiency with simultaneous consideration of all effects of advertising and other methods were not very flexible in that regard. Second, I was measuring advertising efficiency with no priori assumption regarding the functional relationship between advertising budgets and outputs, and DEA did not require me to impose any. Thirdly, DEA can be utilized for different strategic purposes of input minimization and output maximization, and accordingly best fitted my research objectives. The focus of study 1 was mainly on input-side, over-advertising and inefficiency of each media, while in study 2 the focus shifted on output-side, advertising inefficiency in creating each advertising output. Finally, in terms of managerial implication, DEA not only measured advertising efficiency but also provided us with the results of slack analysis and peer analysis. DEA is a very new mainstream in marketing discipline. Specifically, in advertising literature a few studies have applied DEA to determine and analyze the efficiency of advertising practices. The research by Luo and Donthu (2001) was the first study that applied DEA in advertising research and examined the relative advertising efficiencies of leading U.S. advertisers. Färe et al. (2004) estimate the cost efficiency of advertising in the U.S. beer industry and found that most firms have made systematic errors when allocating their advertising dollars among different media. They also revealed a positive relationship between advertising efficiency and overall firm success. Luo and Donthu (2005) compared the two frontier methodologies –DEA and Stochastic frontier model– to benchmark media spending inefficiency. Based on their study, the two methods do not always produce the same results, and accordingly they recommended the use of both frontier methods before reaching a reliable conclusion. They conclude that both analyses are beneficial for benchmarking by providing guidelines for media adjustment of inefficient advertisers. Finally, the results of both methods consistently showed that top 100 marketers' advertising spending in print, broadcast, and outdoor media are not efficient and actually could bring in 20% more sales. Büschken (2007) used DEA to observe the advertising efficiency in German car market and revealed that on average 8% of a brand advertising budget is wasted. Thereafter, he also developed a model for identifying the determinants of brand advertising inefficiency. Kim and Cheong (2009) used DEA to analyze the advertising efficiency of 25 global firms. Pergelova et al. (2010) observed the efficiency of advertising in Spanish automobile industry with the objective to discover the role of internet advertising in the efficiency of the advertising mix. Finally, Jackson (2010) used DEA efficiency as a determinant of strategic group membership in the automobile industry.

Advertising Effects

Advertising is responsible for many critical tasks. First, for an unaware consumer, it has to create brand awareness. If the consumer is aware of the brand but has less knowledge about it, advertising should arouse consumer's interest and knowledge. Thirdly, it has to provide consumer with a list of characteristics and information that is understandable and appealing for the consumer. After creation of such a positive attitude, advertising must convince consumer that the brand is superior to its competitors. Then, it has to prepare consumer mentally, to buy the product. Finally, after creation of such a purchase intention, it has to push consumer toward the final step of purchase. This flow of effects is called advertising hierarchy of effects (Lavidge & Steiner, 1961). Hierarchy of effects in marketing communication is a very long-standing topic which has been in the literature for more than hundred years, appearing in different forms and models. Although this framework has been suggested for all kind of marketing communications, it was mostly being used and focused in advertising researches and practices (Barry, 2002). The earliest hierarchical effect model was proposed by Elmo St. Lewis in 1898. The developed form of this pioneer model (AIDA) was composed of four stages of Attention, Intention, Desire, and Action (Barry, 1987). Later on, Lavidge and Steiner (1961) suggested a more complete hierarchical approach for advertising. There are many other forms of this communication framework with minor modifications and differences (Barry, 1987) but all these models assume that the potential customer passes through three main stages of cognitive, affective and behavioral (or cognition-affect-conation in other terms), in that order (Kotler & Keller, 2012). Barry and Howard (1990) in their review and critique of the advertising hierarchy claimed that this sequence is not applying to all cases, and alternative orders are plausible as well. However, based on literature, this “learn-feel-do” sequence is more appropriate when the audience has high involvement with a product category that is perceived to have high differentiation, such as automobile and house (Kotler & Keller, 2012). Although there are some important critiques to this framework (Weilbacher, 2001) it is still the basis for measuring the effects of advertising and very important to both the practitioner and academic communities (Barry, 2002). The main objective of this study is to evaluate advertising efficiency with respect to all possible outcomes of advertising. Accordingly, all stages in hierarchy of advertising effects are included in our model. Unlike previous research studies, in which final sale was solely recognized or used as the measure of advertising efficiency, I included awareness, attitude and purchase intention as well. Analyzing advertising efficiency solely based on sale can be deficit and problematic, and lead to fallacious results. Overall, the goal of advertising is persuasion; sometimes to persuade consumers to pay attention to the advertisement message (cognition stage), sometimes to change or solidify their attitudes (affective stage), and sometimes to lead them toward purchase (behavior stage) (Barry, 2002). Therefore, in this study, awareness used as a measure of advertising effects in first stage, attitude toward car-models for second stage, and purchase intention and sales volume as two measures of advertising effects in final behavioral stage. It should be noted that in this research I am not about to investigate the relationship between these effects, but I want to incorporate them all in a composite advertising output as a whole, to measure advertising efficiency of various car-models. The objective of study 2 is to investigate the magnitude of each effect in different groups of car-models with different strategies and finding the source of advertising inefficiency in each strategic group. Consequently a brief literature review of strategic group analysis is provided.

Strategic Group Analysis

The term of strategic group first used by Hunt (1972) in his study of U.S. appliance industry. He discovered the existence of asymmetric subgroups within the industry that competed along different dimensions, pushed the industry into a higher degree of competition with higher quality products and lower prices. Porter (1980a) further developed the concept of strategic group by explaining what he called mobility barriers. He believed just like industry entry barriers, there are structural mobility barriers that preventing the entrance of an adjacent competitor into a strategic group which is the middle ground between the industry and the firm. His definition of strategic group as "the group of firms in an industry following the same or a similar strategy along the strategic dimensions" (1980a, p. 129) diffused rapidly in the strategic management literature. Porter (1985) asserts there are three basic businesses strategies - differentiation, cost leadership, and focus - and a company performs best by choosing one strategy on which to concentrate. While various types of organizational strategies have been identified over the years, Porter's generic strategies remained the most commonly identified and supported typology in key strategic management textbooks (Allen & Helms, 2006). These strategies are set as business level and stressed in all departments and actives including marketing and advertising. The differentiation strategy is effectively implemented by providing unique or superior value to the customer through product quality and features, and this quality may be real or perceived based on marketing variables such as brand name, image or fashion (Allen & Helms, 2006). This strategy allows firms to charge a premium price, and since customers perceive the product as unique, they are loyal to the firm and willing to pay this premium price (Porter, 1980a). Cost leadership strategy on the other hand, focuses on gaining competitive advantage by having the lowest price and cost structure in the industry. This strategy can be implemented by mass production, mass distribution, economies of scale, technology, product design, input cost, capacity utilization of resources and access to raw materials (Porter, 1980a). The focus strategy is not a distinct strategy per se and describes the scope over which the company competes based on cost leadership or differentiation, and can be narrow or broad. Porter (1980a, 1996) believed that for long-term profitability firm must make a choice between two dominant strategies rather than being stuck in the middle, because at the frontier production, the trade-off between low-cost and differentiation is very real. In study 2 of this research paper, I used strategic group analysis to identify clusters of car-models with different strategies, and observe their similarities and differences regarding advertising budgeting, effects and efficiency.

Models

This dissertation is composed of two main empirical studies. The first study focus on input side of efficiency, advertising budgeting and media efficiency, while the second study focus on output side of efficiency, advertising effects. The objective of the first study was to track annual level of total and optimal advertising in U.S. car market from 2002 and 2008. I was also interested in finding the overall level of advertising inefficiency and over-expending in each media at industry level. Accordingly, I run input-oriented model of DEA for each year in the time period of 2002 to 2008. In the second study the focus shifts toward advertising effects and benchmarking of advertising efficiency with the objective of output maximization. Thus, I run output-oriented model of DEA over major car-models in U.S. car market during the period of 2004-2006. Thereafter, I utilized strategic group membership to analyze the influence of strategy on advertising effects and efficiency. In this chapter, after a brief overview of DEA, the input-oriented method used in study 1, and output-oriented method used in study 2 will be explained more in details. Thereafter, in the following section, a set of hypotheses that are posited based on review of literature and existing theories will be presented.

Data Envelopment Analysis

DEA is a non-parametric, linear programming formulation for frontier analysis that measures the relative performance of each decision making unit (DMU) by jointly incorporating all of its inputs and outputs into a single composite efficiency score. In engineering sciences the concept of efficiency defined as the ratio of outputs over inputs. When there is only one input and single output, measuring efficiency is as easy as dividing the output by the input. A problem appears when we have more than just one input and output and we have to use the weighted output/input ratio as a measure of efficiency. DEA easily handle this problem by using optimization to identify the weightings of all outputs and inputs, specifically and separately for each DMU, so that the efficiency of each unit is maximized. Let's assume there are n decision making units of DMU_1, DMU_2, … , DMU_n, each producing s outputs by consuming m inputs. For the specific decision making unit of DMU_o (o ranges over $i = 1, 2, \dots, n$) the efficiency rate would be the ratio of weighted sum of outputs (virtual output) over its weighted sum of inputs (virtual input).

(1) $\boldsymbol{Virtual\ output = u_1 y_{1o} + \cdots + u_s y_{so}}$

(2) $\boldsymbol{Vitual\ input = v_1 x_{1o} + \cdots + v_m x_{mo}}$

(3) $\boldsymbol{Efficiency\ of\ DMU_o = \frac{vitual\ output}{virtual\ input} = \frac{weigthet\ sum\ of\ outputs}{weighted\ sum\ of\ inputs} = \frac{\sum_{i=1}^{s} u_i y_{io}}{\sum_{j=1}^{m} v_j x_{jo}}}$

Where v_j is the weight assigned to j-th input and u_i is the weight assigned to i-th output. Now the main step is to define the weights. DEA models use optimizing calculations to derive these weights for inputs and outputs. The essence of DEA models in defining the weights of DMU_olies in maximizing its efficiency rate, subject to the condition that the efficiency rate of any other DMU must not be greater than one, using the same weights. DEA measures the efficiency of each DMU once, and hence requires n optimization, one for each DMU_i to be evaluated. For measuring the efficiency of DMU_o, DEA solves the following fractional programming problem to obtain values for input and output weights.

$$(4) \qquad \max \theta = \frac{u_1 y_{1o} + u_2 y_{2o} + \cdots + u_s y_{so}}{v_1 x_{1o} + v_2 x_{2o} + \cdots + v_m x_{mo}},$$

$$Subject\ to \quad \frac{u_1 y_{1j} + u_2 y_{2j} + \cdots + u_s y_{sj}}{v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj}} \leq 1 \quad (j = 1, \ldots, n),$$

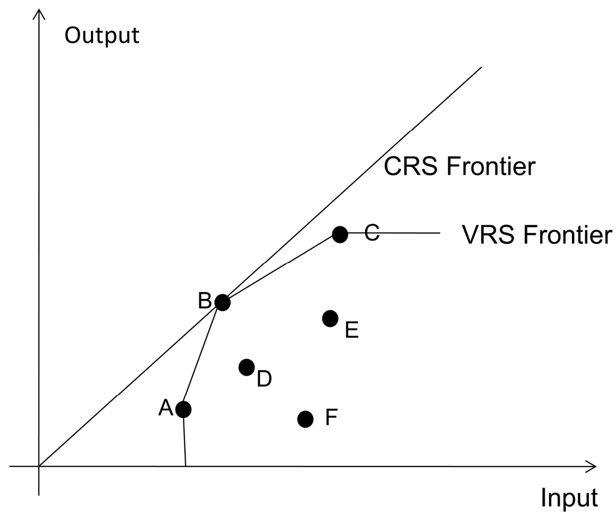
$$v_1, v_2, \ldots, v_m \geq 0,$$

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

To be more elaborate, for each DMU_o, DEA assigns weights to the inputs and outputs in a way that gives the best possible efficiency to that unit ($\max \theta$), reflecting the emphasis that appears to have been placed on them in that particular DMU_o. At the same time, DEA then gives all the other DMUs the same weights and compares the resulting efficiencies with that for the DMU_o. If the focus DMU_o looks better or as good as any other DMUs, it receives a maximum efficiency score of 1 (or 100%); but if with the calculated most favorable weights for the focus DMU_o, some other DMUs looks better, then it will receive a less efficiency score, something between 0 and 1. After N optimization (one for each DMU) all DMUs get their own efficiency scores, and efficient units with efficiency score of 1, form an efficiency frontier that can be used as benchmark for other inefficient units. This is the basic CCR (Charnes, Cooper, Rhodes) model, the first DEA model developed by Charnes et al. (1978) based on Farrell's (1957) ideas of efficiency.

There are many different specifications in data envelopment analysis. Based on scale of productivity, two different assumptions of constant return to scale (CRS) and variable return to scale (VRS) can be made. In CRS methods, we assume that more inputs should lead to proportionally more outputs, while in VRS methods changing all inputs by the same proportion is assumed to lead to more or less proportional output. The following figure illustrates the difference between frontier surfaces in the two models, in the case of single input and single output.

Figure 1: Variable return to scale versus constant return to scale



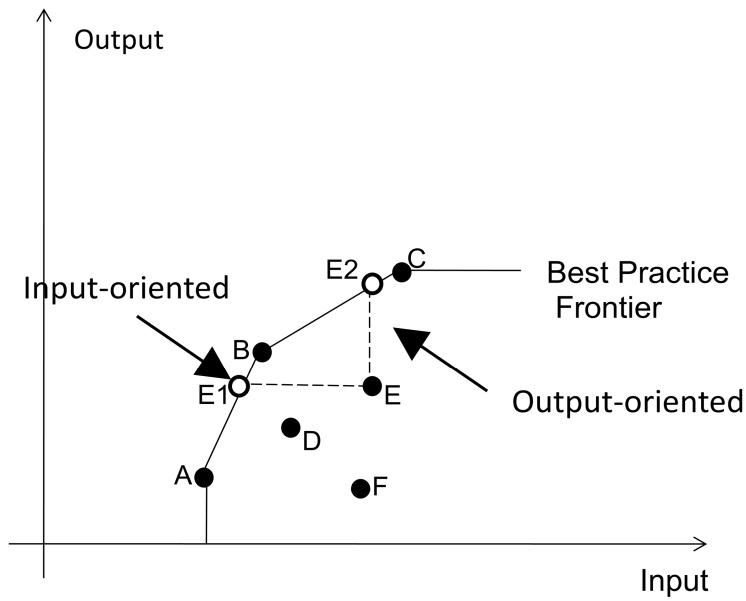
Each point represents a decision making unit. In the CRS method, only unit B is identified as an efficient decision making unit, while in the VRS method, unit A and C are also recognized as efficient best practices.

Mathematically, constant return to scale assumption means if an activity of (x,y) is feasible then for every positive scalar of t, the activity of (tx,ty) is also feasible. However, the VRS models by having their production frontier spanned by the convex hull of existing DMUs, are flexible in this regard and leads to a variable return to scale frontier. Figure 2 illustrates the difference between frontier envelopes in the two approaches, in the case of single input and output. Among basic DEA models, CCR is as an example of

CRS method and BCC (Banker, Charnes, Cooper, 1984) is a VRS method. In advertising context, CRS assumes that the marginal effect of advertising is the same regardless of the advertising budget, while VRS lets the advertising effects to be more for lower budgets and diminish by increase in the size of advertising budget. Since VRS model reflects the typical advertising response function with diminishing returns (Büschken, 2009), this model is assumed to be more applicable for this advertising study.

From a managerial perspective, there can be two different approaches in DEA. Being an inefficient unit, the unit can either produce more output (output-orientated) or use less input (input-oriented) to be more efficient. The goal of output-oriented model is to maximize the outputs, given the level of input, while input-oriented model aims to minimize the inputs achieving the same level of outputs. Although both models produce the same frontier envelop and recognize the same units as efficient, the efficiency score, reference set of efficient DMUs, and slacks (input excess and output shortfalls) would be different in the two approaches. Figure 2 illustrates the difference between two approaches in the case of single input and single output. For inefficient decision making unit of E, input-oriented approach suggests point E1 as an optimal point, while point E2 will be recommended by output-oriented approach.

Figure 2: Input-oriented approach versus output-oriented approach



In study 1, I used input-oriented BCC model, as the focus of the study was mainly on input side of advertising efficiency. Thus, advertising efficiency is measured with the objective of minimizing the advertising budgets, and then advertising inefficiency in each media aggregated at industry level. However, in study 2, I applied output-oriented model since the focus of study was on advertising effects. Accordingly, advertising efficiency is measured with the objective of maximizing outputs, and then strategic analysis is conducted for further interpretation of results. It should be noted that both input-oriented and output-oriented models identify the same DMUs as efficient and therefore produce the same envelopment frontier. However, they are different in determining the optimal level of inputs and outputs for inefficient DMUs below the frontier, and therefore they suggest different level of slacks, over-expenditure in each media and shortfalls in each advertising effect. The input-oriented and output-oriented BCC models used in this study will be explained as follows.

Input-Oriented BCC Model

In input-oriented model the objective is minimizing the inputs with given level of outputs. The dual linear programming for input-oriented BCC model is as follows.

$$\textbf{(5)} \qquad \min \boldsymbol{\theta} - \in (\boldsymbol{e}^T\boldsymbol{s}^- + \boldsymbol{e}^T\boldsymbol{s}^+),$$

$$\begin{aligned} \textbf{\textit{Subject to}}:\ \boldsymbol{s}^- &= \boldsymbol{\theta x_o} - \boldsymbol{X\lambda}\,, \\ \boldsymbol{s}^+ &= \boldsymbol{Y\lambda} - \boldsymbol{y_o}\,, \\ \boldsymbol{e}^T\boldsymbol{\lambda} &= \mathbf{1}, \\ \boldsymbol{\lambda} \geq \mathbf{0}\,&, \boldsymbol{s}^- \geq \mathbf{0}\,, \boldsymbol{s}^+ \geq \mathbf{0}. \end{aligned}$$

Where x_o and y_o are the input and output level of decision making unit under evaluation, $X = [X_{ij},\ i = 1, 2, \dots, m, j = 1,2, \dots, n]$ and $Y = [Y_{ij},\ i = 1, 2, \dots, s, j = 1,2, \dots, n]$ are input and output matrices across all decision making units, $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_n)^T$ is a vector assigned to each individual unit under observation, $s^+$and s^- are vectors of addition input and output variables, $e^T = (1, \dots, 1)$, and $\in$ is a constant greater than zero, normally 10^{-6} or 10^{-8}. Variable return to scale is insured with convexity condition of $e^T\lambda = 1$. The efficiency variable of θ is a reduction scalar that applied to all inputs of DMU_o that is being evaluated. This reduction is simultaneously applied to all inputs, resulting in a radial movement toward the envelopment surface (Charnes et al., 1994). In evaluation of DMU_o, this model seeks a virtual unit characterized by inputs $X\lambda$ and outputs $Y\lambda$, which are a linear combination of inputs and outputs of all DMUs (observations) and which are also better than the inputs and outputs of DMU_o being evaluated (For inputs $X\lambda \leq x_o$ and for outputs $Y\lambda \geq y_o$) . DMU_o is rated efficient if no virtual unit with requested characteristics exist or if the virtual unit is identical with DMU_o ($X\lambda = x_o \; and \; Y\lambda = y_o$). Solving Equation 5, gives the optimal values of θ^* and λ^*. If DMU_o is efficient, then:

i. The value of the efficiency variable θ equals 1 ($\theta^* = 1$).

ii. The value of slacks s^- and s^+ equal 0.

Otherwise, DMU_o is inefficient and the lower θ^*, the lower the efficiency rate is comparing to other DMUs. In this case the optimal values for inputs and outputs will be $X\lambda^*$ and $Y\lambda^*$, and excess in inputs and shortfalls of outputs will be determined by slacks variables of s^- and s^+. Finally, vector of λ^* identifies the reference set of role models for DMU_o; if $\lambda_j{}^*$ is non-zero in vector λ^*, DMU_j will be assigned as a role model for DMU_o, while magnitude of $\lambda_j{}^*$ suggests the suitability of this assignment.

Output-Oriented BCC Model

In the output-oriented BCC model, the focus shifts to output maximization while not exceeding the given input level. The dual linear programming for input-oriented BCC model is as follows.

$$\textbf{(6)} \qquad \max \emptyset + \in (\boldsymbol{e^T s^-} + \boldsymbol{e^T s^+}),$$

$$\textit{Subject to}: \; \boldsymbol{s^-} = \boldsymbol{x_o} - \boldsymbol{X\lambda},$$

$$\boldsymbol{s^+} = \boldsymbol{Y\lambda} - \emptyset \boldsymbol{y_o},$$

$$\boldsymbol{e^T \lambda} = \mathbf{1},$$

$$\boldsymbol{\lambda} \geq \mathbf{0}, \boldsymbol{s^-} \geq \mathbf{0}, \boldsymbol{s^+} \geq \mathbf{0}.$$

All variables are the same as Equation 5. Instead of efficiency scalar of θ, here we have inefficiency scalar of $\emptyset$ that tries to expand output level of y_o as much as constraints allows (Charnes et al., 1994). Based on this model, DMU_o is efficient if the optimal value of $\emptyset$ is equal 1 ($\emptyset^* = 1$), meaning that output level of DMU_o cannot be expanded anymore. Otherwise, if $\emptyset^*$ is greater than 1, DMU_o will be inefficient. Needless to say that $\emptyset^*$ is the inefficiency index and it should be inverted to give the efficiency score.

In our study of advertising efficiency in U.S. car market, each DMU represent a car-model. Inputs are advertising expenditure in each class of media, and outputs are different effects of advertising, thus for each $car - model_o$the input and output vectors will be as shown.

$$\textbf{(7)} \qquad \boldsymbol{x_o} = [\boldsymbol{Broadcast_o}, \boldsymbol{Print_o}, \boldsymbol{Outdoor_o}, \boldsymbol{B2B_o}, \boldsymbol{Internet_o}]^{\boldsymbol{T}}$$

$$\textbf{(8)} \qquad \boldsymbol{y_o} = [\boldsymbol{Awareness_o}, \boldsymbol{Attitude_o}, \boldsymbol{PurcHase - Intention_o}, \boldsymbol{Sale_o}]^{\boldsymbol{T}}$$

Hypothesis Development

Since study 1 is descriptive in nature, no hypothesis is posited in advance. The research objective in this study is to track the total level of over-advertising at industry level over years, and also to reveal the inefficiency of each class of media in this industry. Automobile industry, with high level of advertising, is very competitive in nature. Bushken (2007) in his study of German car market discovered 8% of advertising at company-level has been wasted during 1998-2001. Similarly, I estimate high level of over-advertising in U.S. car market since this market is competitive and saturated by both domestic cars and German and Asian imports. I expect the percentage of over-advertising to be decreased during U.S. economic recession during 2007 and 2008 as firms expected to be more cautious in advertising spending. In terms of media efficiency, Pergelova (2010) in his study of Spanish automobile industry found that internet was the most efficient media in the time period of 2001-2007 in that market while print was the less efficient channel of advertising. Study 1 helps us to find out whether these findings generalizable to U.S. car market or not.

The first part of study 2 is also descriptive in nature. I applied output-oriented DEA to benchmark advertising efficiency of car-models is U.S. car-market. I strived for more details to answer the following questions: (1) what car-models have been more efficient in advertising? (2) what are the inefficiencies of advertising spending in each major medium? (3) what are the shortfalls of each car-model in producing advertising effects? and (4) how can these inefficient car-models become more efficient by enhancing their advertising outputs? Then, in the part, strategic group membership was utilized to analyze the influence of strategy on advertising effects and efficiency. In this part, I attempted to reveal possible differences in advertising practices and efficiency of car-models with different strategies. To do so, I had to conduct a strategic group analysis, to break the industry into subgroups of car-models pursuing common strategies. In terms of methodology, a typical strategic group analysis utilizes some sort of cluster analysis on a set of strategic variables (Harrigan, 1985). Strategic dimensions of price and quality have been used as the bases of clustering based on the purpose of study. Porter's generic strategies are significantly different in terms of these two dimensions. There is always a tradeoff between price and quality. While main objective in differentiation strategy is producing high-quality products, cost-leadership strategy focuses on delivering lower priced products (Porter, 1985). I believed that differentiation strategy is attributed with high level of price and quality, while cost-leadership strategy produces car-models with relatively lower price and quality. Furthermore, I assumed car-models that use a combination of both strategies would probably end with a medium range of price and quality indexes. After a brief review of theories and findings in each strategic dimension, our hypotheses regarding advertising differences between dominant strategies will be presented.

Price

Price has always operated as a major determinant of customers' choice, and this is significantly more relevant in durable high involvement products such as cars. Although in modern marketing, the role of non-price factors has increased dramatically, price still remained a critical element of marketing mix; unlike all other elements that produce costs, price is the only element that brings revenue (Kotler & Keller, 2012). Kotler and

Keller (2012) identified five major objectives for pricing including survival, maximizing current profit, maximizing market share, maximizing market skimming and product-quality leadership. Erickson and Johansson (1985) claimed that price plays a multidimensional role in consumer's evaluation process of product alternatives. They indicated that two of main roles are “price as constraint” and “price as a signal of quality”. In the first role, from an economic perspective, price of a product limits available budget for spending on other goods and therefore can be viewed as a constraint. This role has been become even more serious after the recent economic downturn. Many customers found that they are unable to sustain their life style, began to buy more for need than desire and trade down in price more frequently (Kotler & Keller, 2012). Erickson and Johansson (1985) in their study of automobile industry found that price, with its budget-constraint role, has a direct negative effect on the probability of purchasing a given car. From another perspective, price also works as a signal of quality. This topic has been well examined in the literature. First, Scitovsky (1945) claimed that consumers associate a higher quality product with a higher price, and in a later study Leavitt (1954) found that consumers also associate higher prices with higher quality, in a reverse manner. Erickson and Johansson (1985) confirmed this reciprocal relationship by finding that higher priced cars are perceived to possess higher quality, likewise, high quality cars are perceived to be higher priced. Moreover, based on the results of a meta-analysis, Rao et al. (1989) showed that there is a significant positive relationship between price and perceived quality. Price as a signal of quality can also influence attitude toward the car. As I will discuss later in this paper, quality is a determinant of attitude toward product, and price as a signal of quality, can have an indirect effect on attitude. Erickson and Johansson (1985) confirmed a weak indirect effect of price on attitude. Additionally, there is a general positive attitude toward luxury products among individuals, although they may not consider themselves as potential customers.

Quality

Based on American Society definition "quality is the totality of features and characteristics of a product or service that bear on its ability to satisfy stated or implied needs" (Kotler & Keller, 2012, p.131). Although price and quality are found to be correlated to some extent, in both literature and this study, I used quality as a separate dimension as I believed the combination of the two, will lead us to identify more specific and accurate strategic clusters. Moreover, the role of price as a signal of quality is limited to the availability of other information (Kotler & Keller, 2012; Erickson & Johansson, 1985). Finally, from consumers' perspective, customers take both price and quality into account as they form an overall evaluation about a product; they evaluate each (e.g. price) in the light of the other (given quality) to avoid a confounding of the two (Fornell, 1992). It can be predicted that high-quality cars should have greater positive attitude among customers. Firstly, the effect of quality on consumer satisfaction is well discussed in the literature (Anderson et al. 1994; Anderson & Fornell 2000; Fornell et al., 1996). This satisfaction leads to consumer loyalty and strong positive post-purchase attitude among buyers, which consequently increases word-of-mouth type of advertisements and overall awareness of the product. Moreover, quality, with two distinct dimension of (1) fitness for use – extent to which product's features meet the needs of customers- and (2) reliability – extent to which the product is free from deficiencies (Anderson et al. 1994) will lead to significant pre-purchased attitude toward the product. Rosecky and King (1996) also identified quality as a determinant of attitudes toward products in their study of automobile industry.

Hypotheses

Based on previous literature review and existing theories I developed the following hypotheses in study 2. Generally, in differentiation cluster, there is insulation against competitive rivalry as a result of brand loyalty and price insensitivity among customers (Porter, 1980b). Accordingly, there is a lower level of competition. On the other hand, there is strong competitive force within cost-leadership strategic group (Porter, 1980b). In this group of car-models, price competition is not an appropriate form of rivalry as it may leave the entire strategic group and even the whole industry worse off. As indicated by Porter (1980b) price-cuts can be easily matched by competitors, and once matched it will bring lower revenue for all firms. This may push low-cost car-models toward an advertising battle instead of competition over lower prices. Firms use advertising as a form of information function to signal their quality and achieve long-term profitability (Nelson, 1974). Therefore, for this group of car-models, advertising can substantially compensate for the low level of quality. Therefore, I hypothesize:

> ***H1:*** *Total advertising expenditure should be significantly higher for cost-leadership cluster and lower for differentiation cluster.*

Cost-leadership and differentiation clusters seem to obtain awareness through different paths. In differentiation cluster, product quality and features plays a significant role in obtaining awareness. Quality, by creating satisfaction among customers that ultimately leads to customer loyalty (Anderson et al. 1994; Anderson & Fornell 2000), increases word-of-mouth type of advertisements and overall awareness of the car-model. On the other hand, in cost-leadership cluster, car-models use intensive advertising to create awareness, and it usually works fine since awareness is the initial outcome of advertising in hierarchy of effects. For car-models with combined strategy, both medium level of quality and medium level of advertising can be the source of awareness. Accordingly, I expect no significant difference between levels of awareness among strategic clusters and hypothesize:

> ***H2a****: There is no significant difference between awareness of car-models with cost-leadership and differentiation strategy.*

However, advertising inefficiency in producing awareness should be relatively lower for differentiated car-models. Thanks to their high quality, these car-models are expected to produce higher level of awareness with lower advertising budget. Accordingly, I propose:

> ***H2b:*** *Advertising inefficiency in producing awareness should be lower for car-models with differentiation strategy and higher for cost-leadership strategy*.

Regarding positive attitude among customers, differentiation strategy has competitive advantage over cost-leadership strategy. Based on literature, product quality creates satisfaction that is ultimately transformable to strong positive post-purchase attitude among buyers (Anderson et al. 1994; Anderson & Fornell 2000; Fornell et al., 1996). Moreover, as indicated earlier, quality, with two distinct dimension of (1) fitness for use and (2) reliability will lead to significant pre-purchased attitude toward the product (Anderson et al. 1994). Rosecky and King (1996) also identified quality as a determinant of attitudes toward products in their study of automobile industry. Accordingly, differentiated car-models, with higher level of quality, tend to possess greater level of positive attitude among customers. Moreover, higher price of these car-models, as a signal of quality, can have an indirect effect on attitude. Erickson and Johansson (1985) confirmed a weak positive effect of price on attitude. Overall, there is a greater positive attitude toward high-quality luxury car-models among individuals, although they may not consider themselves as potential customers. Based on these findings, I hypothesize:

> ***H3a**: Positive attitude toward car-models is significantly higher for differentiation strategy and lower for cost-leadership strategy.*

In terms of advertising inefficiency, it is not aberrant to expect that advertising shortfalls in creation of positive attitude to be higher for car-models with low cost strategy. These car models with greater advertising budget possess less positive attitude. Thus, I propose:

> ***H3b**: Advertising inefficiency in producing positive attitude should be higher for cost-leadership strategy and lower for differentiation strategy.*

Price is a determinant factor in behavior stage of purchase funnel. This is specifically more important for high involvement product category, with low frequency of purchase. Erickson and Johansson (1985) found that price, with its budget-constraint role, has a direct negative effect on the probability of purchasing a given car. Accordingly, I expect higher level of purchase intention for car-model with cost-leadership strategy. For car-models with differentiation strategy, not all customers willing or able to pay the required premium prices, even though they may acknowledge the superiority of the cars (Porter, 1980b). Consequently, I propose:

H4a: *Purchase intention is significantly higher for car-models with cost-leadership strategy and lower for car-models with differentiation strategy.*

Due to the negative effect of price on purchase intention, advertising of differentiated car-models seems to be less efficient in producing purchase intention. Accordingly, I hypothesize:

H4b: *Advertising inefficiency in producing purchase intention should be higher in differentiation cluster and lower in cost-leadership cluster.*

In terms of sales volume, cost-leadership strategy by definition possesses greater level of sales and market share. According to Porter (1980b), achieving a low cost position requires relatively higher sales volume and market share, while differentiation strategy requires a perception of exclusivity which is incompatible with high market share. For cost-leadership car-models advertising seems relatively more efficient in producing sales volume due to the positive effect of lower prices. On the other hand, I expect most of the advertising inefficiency of differentiated car-models to be related to behavior stage. Accordingly, I hypothesize:

H5: *Advertising inefficiency in producing sales volume should be relatively higher for differentiation cluster and lower for cost-leadership cluster.*

Finally, since advertising of cost-leadership cluster, tends to outperform on behavior stage, and advertising of differentiated car-models tend to be more productive on affective stage, I expect no meaningful difference in advertising efficiency of these strategic groups, and propose:

H6: *There is no significant difference between advertising efficiency of car models with differentiation and cost-leadership strategies.*

Methodology

Data

In this research study, I focused on major car-models in U.S. car market, including 83 car-models from 29 brands. The data was gathered from different sources. The following table shows the descriptive statistics of our variables across all 83 car-models.

Table 1: Descriptive statistics of data

		Advertising Expenditure (000$)						Advertising Effects					
		Boradcast	Print	Outdoor	B2B	Internet	Overall	Awareness	Attitude	Purchase Intention	Sales Volume	Quality	Price($)
Average (2004-2006)	Sum	420,187	156,218	272	344	13,392	590,412	5,026	4,451	36	1,457,948	305	2,622,336
	Mean	5,062	1,882	3	4	161	7,113	61	54	0	17,566	4	31,594
	Min	0	0	0	0	0	2	15	12	0	407	2	10,642
	Max	37,744	9,762	123	94	848	47,883	93	83	3	108,928	5	95,412
2002	Sum	524,878	183,983	377	302	4,578	714,118	4,725	4,424	33	1,418,723		
	Mean	6,480	2,271	5	4	57	8,816	58	55	0	17,515		
	Min	0	0	0	0	0	0	8	11	0	337		
	Max	35,423	11,682	163	52	755	46,779	94	84	3	108,077		
2003	Sum	533,930	205,781	490	318	7,830	748,349	5,010	4,508	35	1,455,858		
	Mean	6,433	2,479	6	4	94	9,016	60	54	0	17,540		
	Min	0	0	0	0	0	0	14	11	0	526		
	Max	34,429	12,408	320	73	1,101	40,454	93	84	3	103,993		
2004	Sum	479,466	188,757	684	218	13,020	682,145	5,041	4,489	35	1,464,286		
	Mean	5,777	2,274	8	3	157	8,219	61	54	0	17,642		
	Min	0	0	0	0	0	0	13	12	0	446		
	Max	39,886	12,217	361	53	1,394	52,783	91	84	3	106,748		
2005	Sum	426,298	161,482	9	442	10,789	599,020	5,031	4,448	37	1,467,391		
	Mean	5,136	1,946	0	5	130	7,217	61	54	0	17,679		
	Min	0	0	0	0	0	0	14	13	0	330		
	Max	41,474	14,240	8	107	1,313	56,001	94	82	3	107,926		
2006	Sum	354,796	118,415	123	372	16,366	490,073	5,006	4,417	37	1,442,168		
	Mean	4,275	1,427	1	4	197	5,904	60	53	0	17,376		
	Min	0	0	0	0	0	0	16	13	0	328		
	Max	43,180	10,943	110	126	1,398	53,565	95	85	3	112,111		
2007	Sum	360,859	143,424	31	536	23,539	528,390	4,904	4,397	36	1,397,852		
	Mean	4,348	1,728	0	6	284	6,366	59	53	0	16,842		
	Min	0	0	0	0	0	0	0	0	0	0		
	Max	48,830	11,281	16	161	3,626	61,710	92	84	3	118,277		
2008	Sum	367,483	106,784	17	299	30,047	504,629	4,971	4,828	40	1,225,097		
	Mean	4,428	1,287	0	4	362	6,080	60	58	0	14,760		
	Min	0	0	0	0	0	0	0	0	0	0		
	Max	33,108	17,873	17	110	6,254	55,114	95	86	4	109,154		

Advertising expenditure data was obtained from TNS Media Intelligence. This dataset records automobile companies' spending on 18 different media, including cable television, satellite television, network television, spot television, local radio, national sport radio, network radio, magazines, local magazines, newspapers, national newspapers, outdoor, Sunday magazines, syndications, business-to-business, magazines and newspapers targeted toward Hispanic populations, and internet advertising. These media are classified into five broad categories: Broadcast, Print, Outdoor, B2B and Internet. Our advertising variables are organized in quarterly basis. Since for some car-models there were missing observations in some quarters, I used the average of four (or all existing) quarters rather than sum, for each year. For consistency, I followed the same approach for all other variables such as sales volume and communication effects. Overall, our advertising variables represent average quarterly expenditure (000$) of car-models in those five aforementioned classes of media, for each year from 2002 to 2008. For study 2, I used average of these variables during period of 2004-2006.

The data regarding communication effects of advertising is obtained from GfK. GfK, by running several surveys and studies, has tracked awareness, attitude and purchase intention of car-models in U.S. market. Awareness and Attitude were measured in the scale of 1-100 while purchase intention was measured in the scale of 0-5. These measures are gathered on quarterly bases (sometimes semi-annually), and for this research I used the average of four (or all existing) quarters per year, for each variable.

For sales volume information, I used the dataset gathered by CNW Marketing Research Inc. Again sales variables, indicate the average of quarterly unit sold in each year. Finally, for measuring quality of car-models I relied on IQS (Initial Quality Study) index of quality, provided by J.D. Power and Associates. This quality index is based on both mechanical and design aspects of quality.

Study 1 - Annual track of over-advertising and media inefficiency in U.S. car market from 2002 to 2008

For this study, I applied input-oriented BCC model as a VRS method, and EMS software is used for that purpose. The main objective of the study was to reveal the overall level of over-advertising (at model-level) in the industry and share of inefficiency in each class of media. As explained earlier, input-oriented method of DEA chosen for this part because the focus of the study was more on budgeting side of advertising. Equation 5 has been run over 83 car-models under study for year 2002, with consideration of five input variables (broadcast, print, outdoor, B2B and internet advertising expenditures), and four outputs (awareness, attitude, purchase intention and sales). Since the focus of the study was at macro level, advertising efficiency at industry-level, I did not go through the details of benchmarking results for each car-model. Instead, I accumulated over-expenditure of car-models in each media. This gives us the dollar amounts that are over-spent in each media. I also calculated the percentage of over-spending in each media which is the ratio of over-spending over total budget of each media across all car-models. To capture the total level of advertising inefficiency, over-expenditure in those five media were added up again, and share of each media in total over-advertising was calculated. The same procedure is conducted for subsequent years up to year 2008.

Study 2 - Strategic group memberships to analyze influence of car-models strategies on advertising effects and efficiency

In this study, first, I benchmark advertising efficiency of car-models in U.S. car market during the period of 2004-2006. I applied output-oriented BCC model of DEA presented in Equations 6, because the focus of the study was on advertising effects. The result of output-oriented DEA reveals the advertising efficiency of each car-model with the objective of output maximization given its level of advertising budget. For this study, I looked over a wider time interval, the three-year time period of 2004 to 2006. Three-year time period is an appropriate time frame for marketing auditing as it sufficient to capture both short and long-term effects (Alexander Hamilton Institute, 1994). The results of DEA provides us with details regarding (1) efficient car-models in advertising, (2) over-expenditure of each car-model in each major medium (3) shortfalls of each car-model in producing each advertising effect and (4) unique reference set of best practices for each car-model to emulate.

In the next step I utilized strategic group membership to reveal the influence of strategy on advertising effects and efficiency. This helps us to interpret the results of output-oriented DEA and to find out whether advertising efficiency of car-models with different strategies are significantly different in producing each advertising effect (%shortfalls in each output). Price and quality has been used as our strategic dimensions for bases of strategic group membership. K-means cluster analysis is conducted over 83 car-models under study. I used Calinski index to find the optimal number of clusters. Among different number of clusters, having 3 clusters suggested by the data (maximized Calinski index and explained enough variance between clusters) and supported our objective (each cluster representing a distinct strategy). Based on this cluster analysis, strategic groups of car-models are formed. In the next step, analysis of variance (ANOVA) is utilized for testing hypotheses regarding the mean differences of advertising variables in the three formed clusters, and independent planned t-test (one-tail) to explore the differences between two dominant strategies.

Discussion of Results

Results of Study 1

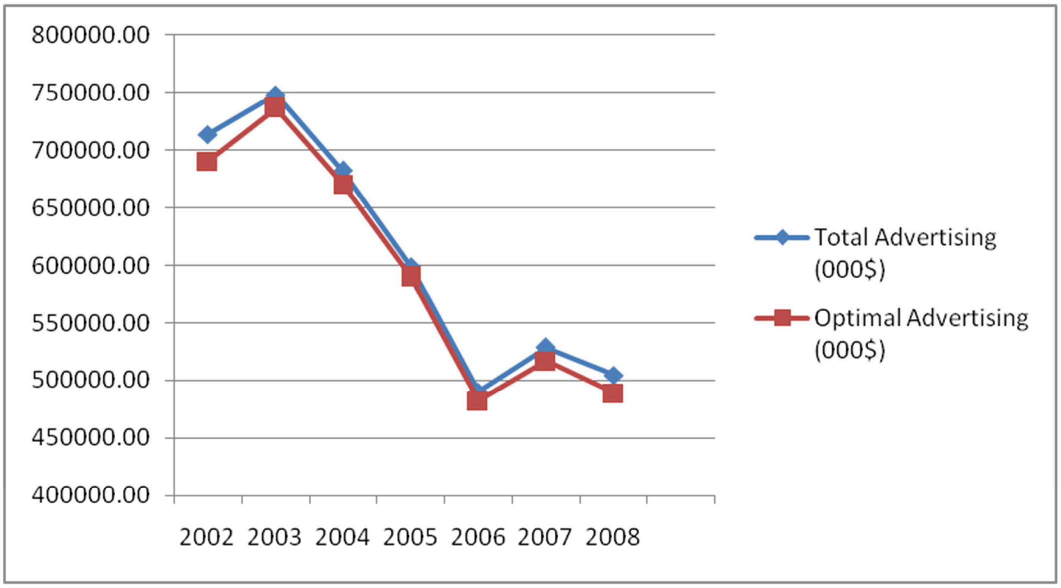
The aggregated level of total advertising expenditure and optimal advertising across all car-models are depicted in Table 2.

Table 2: Aggregated level of advertising expenditure in U.S. car market

	Total Advertising (000$)	Over-Advertising (000$)	Optimal Advertising (000$)	Over-Advertising %
2002	714118	23653	690466	3.3%
2003	748349	11584	736765	1.5%
2004	682145	11832	670313	1.7%
2005	599020	8983	590037	1.5%
2006	490073	7618	482454	1.6%
2007	528390	11384	517006	2.2%
2008	504629	15563	489066	3.1%
AVG	4266724	90616	4176107	2.1%

As illustrated in Figure 3, the total advertising expenditure has decreased gradually from 2002 to 2008. Tracking advertising expenses in this period shows that there was an upward trend from 2002 to 2003, reaching its maximum level in 2003. This can be attributed to the economic recovery after the U.S. recession in 2001. From 2003 onwards, there was a significant descending trend in advertising, and in period of 2006-2008, advertising expenditure was at its lowest level. This may also be related to the economic recession started in 2007. This downward trend in advertising expenditure may implicitly indicates that firms became more concerned about advertising expenditures and tried to minimize their budgets as much as possible.

Figure 3: Annual track of advertising expenditure in U.S. car market



However, cutting the advertising budgets will not necessarily lead to higher advertising efficiency. Figure 4 displays the average percentage of over advertising in each year. The downward shift from 2002 implies that the firms spent advertising budgets more efficiently in years 2003 to 2006. After 2002, the highest level of advertising inefficiency reported for years 2007 (2.2%) and 2008 (3.1%). This is very surprising since in this period, advertising expenditure was at its lowest rates comparing to previous years (except for year 2006). Assuming all other factors remained constant, this may implies that firms became more capable in transforming advertising budgets into communication and sales outputs. In fact, this recent upward trend in over-advertising, more seriously, urges the application of advertising benchmarking by the firms. In total, our results reported 2.1% of over-advertising at model-level in U.S. car market, for the time period of 2002-2008.

Figure 4: Over-advertising percentage in U.S. car market

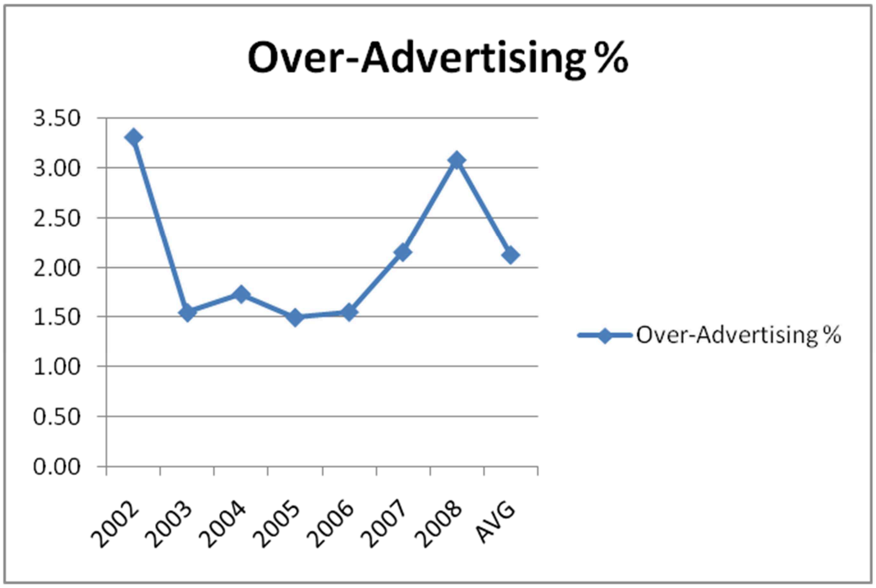


Table 3 shows the sum of advertising expenditures and slacks, across all 83 car-models in each media. It also reports the percentage of over-advertising (%Slack) in each media and share of each media in advertising inefficiency (%Share) for that year. Generally, most of the advertising inefficiency occurred in broadcast advertising (except in years 2004 and 2007 which was in Print advertising); on average 58.7 % of over-advertising was in this media that accounted for 1.9% of its budget. Print media had the second highest share of advertising inefficiency (except in years 2004 and 2007 which was the first), with average of 34% share of inefficiency and 2.4% of its budget being over-spent. Outdoor and B2B channels had the less share of inefficiency; however the percentage of their slacks (portion of budget being over-spend) was significantly higher. The budget of internet, as a new media, increased rapidly from 2002 to 2008 (by more than 600%). Although internet's share of inefficiency was moderate on average (6.9%), in year 2008

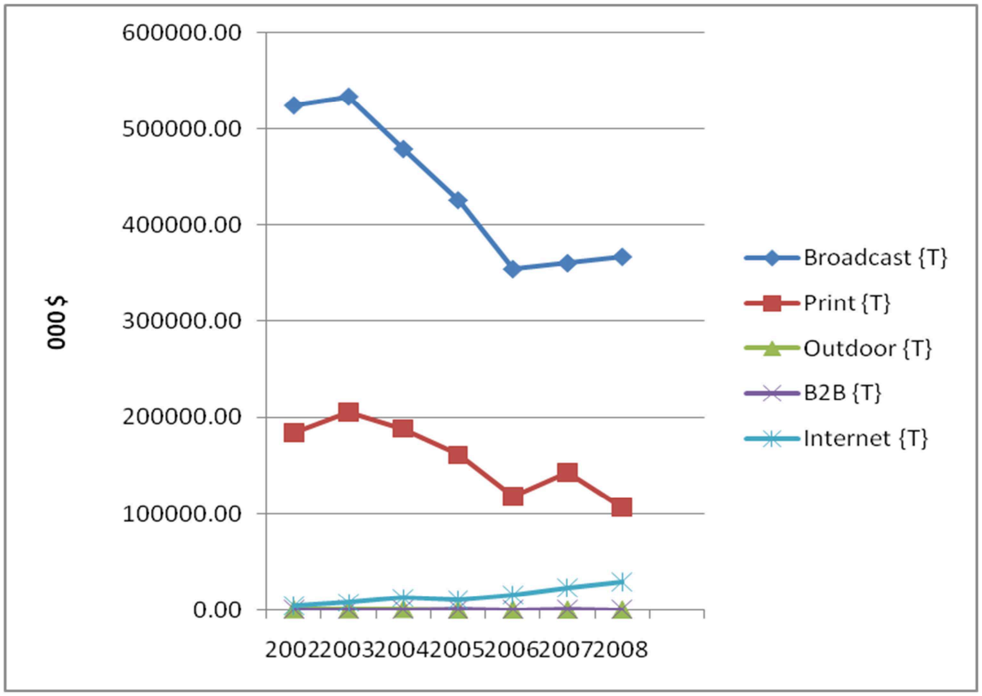
Table 3: Analysis of media efficiency

		2002	2003	2004	2005	2006	2007	2008	Average
Broadcast									
	Slack	22371	5211	1896	6115	6375	3141	11772	8126
	Total	524878	533930	479466	426298	354796	360859	367483	435387
	%Slack	4.3%	1.0%	0.4%	1.4%	1.8%	0.9%	3.2%	1.8%
	%Share	94.6%	45.0%	16.0%	68.1%	83.7%	27.6%	75.6%	58.7%
Print									
	Slack	1031	5469	9786	2286	226	7672	1255	3961
	Total	183983	205781	188757	161482	118415	143424	106784	158375
	%Slack	0.6%	2.7%	5.2%	1.4%	0.2%	5.3%	1.2%	2.4%
	%Share	4.4%	47.2%	82.7%	25.5%	3.0%	67.4%	8.1%	34.0%
Outdoor									
	Slack	24	136	59	3	1	1	1	32
	Total	377	490	684	9	123	31	17	247
	%Slack	6.5%	27.9%	8.6%	31.0%	0.7%	4.8%	4.5%	12.0%
	%Share	0.1%	1.2%	0.5%	0.0%	0.0%	0.0%	0.0%	0.3%
B2B									
	Slack	6	69	41	0	11	9	6	20
	Total	302	318	218	442	372	536	299	355
	%Slack	1.9%	21.8%	18.7%	0.0%	2.9%	1.7%	1.9%	7.0%
	%Share	0.0%	0.6%	0.3%	0.0%	0.1%	0.1%	0.0%	0.2%
Internet									
	Slack	231	698	50	578	1005	559	2529	807
	Total	4578	7830	13020	10789	16366	23539	30047	15167
	%Slack	5.0%	8.9%	0.4%	5.4%	6.1%	2.4%	8.4%	5.2%
	%Share	1.0%	6.0%	0.4%	6.4%	13.2%	4.9%	16.3%	6.9%

* Slack and Total in 000$

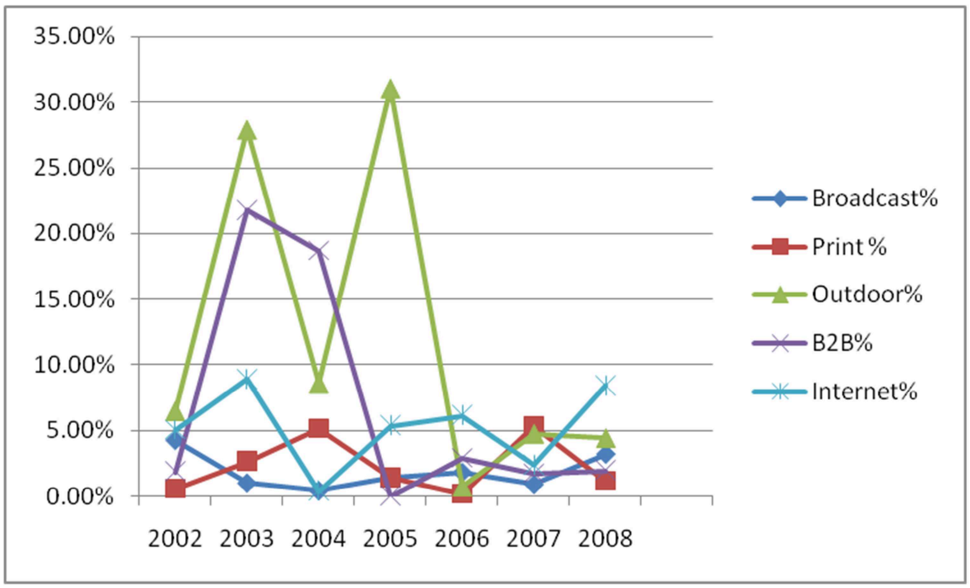
it was recognized at the most inefficient media (16.3 % share of inefficiency with 8.4% of over-advertising). Figure 5, depicts the trend of advertising expenditure in each media. While the budgets of broadcast, print and outdoor media decreased dramatically, B2B advertising remained constant and internet advertising increased significantly.

Figure 5: Advertising expenditure in each class of media in U.S. car market



The percentage of over-spending in each media displayed in Figure 6. Overall, Outdoor seems to be the less efficient media with the highest percentage of over-advertising. This may be the underlying reason that budget of this media has decreased significantly in recent years of study. B2B advertising, on the other hand became relatively more efficient in last years of study. Internet was the most inefficient media with highest over-advertising percentage in 2008. This seems to be the point that internet advertising became a prevalent marketing practice in U.S. car-market, and as a result of this huge investment, its efficiency decreased dramatically. Future studies should focus more closely on advertising efficiency of internet as a new media. In terms of managerial implications these findings helps international brands to adjust advertising strategies relative to the market they are competing over. For instance study of automobile industry in German market (Bushken, 2007) and Spanish market (Pergelova, 2010) show different results regarding the advertising efficiency of each media. Thus, auto makers have to be aware of advertising efficiency of each media in each market, and makes advertising decisions accordingly.

Figure 6: Over-advertising percentage in each class of media in U.S. car market



Results of Study 2

The advertising efficiency scores of car-models in the time period of 2004-2006 are reported in Table 4. As indicated in the table, 32 of these 83 car-models obtained the 100% score, being recognized as efficient advertisers. Overall, there was an average advertising efficiency score of 87% in this industry that is relatively high. For some makers such as Honda, Toyota, BMW and Mercedes Benz, all car-models under the umbrella of those brands were efficient advertisers, whereas in some makers such as

SAAB, Jaguar and Audi, all car-models were found to be relatively inefficient. This may suggest the influence of corporate advertising strategies on car-models' advertising efficiency. Future studies can include corporate level variables such as company-level advertising or number of car-models under the same corporate brand, as control variables.

Table 4: DEA efficiency scores of car-models in U.S. car market

Brand	Car-Model	Efficiency Score	Brand	Car-Model	Efficiency Score	Brand	Car-Model	Efficiency Score
ACURA	RL	78.85%	HYUNDAI	Accent	100.00%	NISSAN	350Z	95.98%
	RSX	60.23%		Elantra	73.74%		Altima	100.00%
	TL	92.72%		Sonata	59.86%		Maxima	96.30%
	TSX	78.16%		Tiburon	86.94%		Sentra	82.70%
AUDI	A4	78.08%	JAGUAR	XJ	72.31%	PONTIAC	GrandPrix	100.00%
	A6	73.76%		XK	73.58%		Vibe	73.82%
	A8	81.94%		Xtype	70.84%	PORSCHE	911Carrera	100.00%
BMW	3series	100.00%	KIA	Optima	47.73%		Boxster	98.74%
	5series	100.00%		Rio	100.00%	SAAB	93	55.79%
	7series	100.00%	LEXUS	ES	95.62%		95	57.73%
	Z3_Z4	88.65%		GS	98.12%	SATURN	Ion	85.81%
CADILLAC	CTS	78.80%		IS	91.68%	SUBARU	Impreza	47.69%
CHEVROLET	Corvette	100.00%		SC	100.00%		Legacy	100.00%
	Impala	100.00%	LINCOLN	Lsseries	78.47%	SUZUKI	Aerio	100.00%
	Malibu	86.99%		TownCar	100.00%		Forenza	83.69%
	MonteCarlo	100.00%	MAZDA	Mazda6	68.44%	TOYOTA	Avalon	82.05%
CHRYSLER	300M	60.36%		MX5Miata	78.85%		Camry	100.00%
	Ptcruiser	100.00%	MERCEDES BENZ	Cclass	92.84%		Corolla	100.00%
	Sebring	82.94%		Clclass	100.00%		Prius	100.00%
DODGE	Viper	100.00%		CLKclass	100.00%	VOLKSWAGEN	Golf_GTI	74.73%
FORD	Focus	88.75%		Eclass	100.00%		Jetta	82.52%
	Mustang	100.00%		Sclass	100.00%		NewBeetle	89.41%
	Taurus	100.00%		Slclass	100.00%		Passat	65.59%
HONDA	Accord	100.00%		SLKclass	86.08%	VOLVO	40series	77.02%
	Civic	100.00%	MERCURY	GrandMarquis	100.00%		60series	89.46%
	S2000	100.00%	MITSUBISHI	Eclipse	92.93%		70series	85.54%
INFINITI	G35	82.79%		Galant	60.66%		80series	93.23%
	M35_45	72.61%		Lancer	100.00%	Average		87.13%

The results of peer analysis are reported in Tables 5. As shown in the tables, DEA suggested a set of best-practices as role-models for each inefficient car-model. The numbers in parenthesis are λ-coefficients in Equation 3. As explained before, for each inefficient car-model a linear combination of efficient car-models are identified as an optimal role model, thus the magnitude of λ-coefficients implies the relative suitability of that efficient car-model as a role-model for the inefficient car-model under evaluation. In total, 5series, Corvette, Accord, ClKclass and GrandPrix were most frequently assigned as best practices for inefficient car-models.

Table 6 shows the output slacks of output-oriented model. Percentage of shortfalls in each advertising effects is reported rather than actual values for better illustration. A quick glance at the results indicates that output inefficiencies mostly related to shortfalls in purchase-intention and sales volume. Some of these shortfalls are too big to be resolved easily. This is specifically more difficult for sales volume; for instance, based on the results, Jaguar XJ and SAAB 95 have to increase their sales by more than 300% with the same level of advertising budget to be efficient. Overall, inefficient car-models in U.S. car market has to create 3.6% more awareness, 3.7% more positive attitude, 31.6% more purchase intention and 9.1% more sales volume to be efficient advertisers. In terms of managerial implication, these results indicate that generally, most of advertising inefficiency in terms of creating advertising outputs is related to behavior stage rather than cognitive and affective stage. At industry level speaking, advertising seems to be relatively less efficient in persuading customers to commit to purchase. This may implicitly reflects the relative incapability of advertising as a marketing practice, in creating immediate behavioral effects comparing to price promotions, something that has been well discussed in the literature. However, this finding might not be generalizable to other industries and replication of this study for lower-involvement product categories will shed light in that direction.

Table 5: Peer analysis of output-oriented model

Car-Model	Output - Oriented Reference Set	Car-Model	Output - Oriented Reference Set
3series	**Efficient**	**Impreza**	5series (0.2) ClKclass (0.2) GrandPrix (0.4)
300M	3series (0.1) Accord (0.2) Camry (0.1) Prius (0.3)	**Ion**	3series (0.1) GrandPrix (0.8)
350Z	911Carrera (0.1) ClKclass (0.1) GrandMarquis (0.5) Viper (0.1)	**IS**	5series (0.8)
40series	5series (0.7) 7series (0.2)	**Jetta**	Accord (0.2) Corvette (0.7)
5series	**Efficient**	**Lancer**	**Efficient**
60series	ClKclass (0.8)	**Legacy**	**Efficient**
7series	**Efficient**	**Lsseries**	911Carrera (0.2) MonteCarlo (0.6)
70series	ClKclass (0.7) Corvette (0.1)	**M35_45**	5series (0.8) Accord (0.1)
80series	ClKclass (1.0)	**Malibu**	Corvette (0.2) Impala (0.7)
911Carrera	**Efficient**	**Maxima**	5series (0.2) Corvette (0.3) Prius (0.3)
93	5series (0.7) Sclass (0.2)	**Mazda6**	3series (0.39) 5series (0.22) GrandPrix (0.39)
95	5series (0.3) ClKclass (0.2) Corvette (0.2) Viper (0.1)	**MonteCarlo**	**Efficient**
A4	5series (0.7) Prius (0.2)	**Mustang**	**Efficient**
A6	5series (0.4) 7series (0.1) Corvette (0.2) Sclass (0.1)	**MX5Miata**	Corvette (0.4) Viper (0.5)
A8	911Carrera (0.1) ClKclass (0.8)	**NewBeetle**	Corvette (0.4) MonteCarlo (0.5)
Accent	**Efficient**	**Optima**	Corvette (0.3) GrandPrix (0.6)
Accord	**Efficient**	**Passat**	5series (0.1) Accord (0.4) Corvette (0.4)
Aerio	**Efficient**	**Prius**	**Efficient**
Altima	**Efficient**	**Ptcruiser**	**Efficient**
Avalon	5series (0.7) Corolla (0.1) Prius (0.1)	**Rio**	**Efficient**
Boxster	911Carrera (0.1) ClKclass (0.3) Viper (0.5)	**RL**	5series (1.0)
Cclass	5series (0.3) Accord (0.1) Sclass (0.5)	**RSX**	5series (0.1) 7series (0.4) Corvette (0.2)
Camry	**Efficient**	**Sclass**	**Efficient**
Civic	**Efficient**	**S2000**	**Efficient**
Clclass	**Efficient**	**SC**	**Efficient**
CLKclass	**Efficient**	**Sebring**	GrandMarquis (0.1) GrandPrix (0.6) Legacy (0.1)
Corolla	**Efficient**	**Sentra**	5series (0.2) Corvette (0.1) Taurus (0.4)
Corvette	**Efficient**	**Slclass**	**Efficient**
CTS	3series (0.4) 5series (0.1) Corvette (0.3)	**SLKclass**	5series (0.1) 7series (0.8)
Eclass	**Efficient**	**Sonata**	Accord (0.3) Corolla (0.2) Corvette (0.3)
Eclipse	5series (0.5) Viper (0.3)	**Taurus**	**Efficient**
Elantra	ClKclass (0.1) GrandPrix (0.1) Rio (0.1) Taurus (0.6)	**Tiburon**	Aerio (0.1) ClKclass (0.4) Rio (0.3)
ES	5series (0.5) Corolla (0.1) Sclass (0.3)	**TL**	3series (0.2) 5series (0.5) GrandPrix (0.1)
Focus	Camry (0.2) Corvette (0.3) Taurus (0.3)	**TownCar**	**Efficient**
Forenza	GrandPrix (0.1) Legacy (0.8)	**TSX**	5series (0.4) 7series (0.2) Corvette (0.1) Prius (0.1)
G35	5series (0.3) Accord (0.2) Sclass (0.4)	**Vibe**	ClKclass (0.2) GrandPrix (0.5) Rio (0.2)
Galant	5series (0.2) Corvette (0.5) Ptcruiser (0.1)	**Viper**	**Efficient**
Golf_GTI	Corvette (0.2) MonteCarlo (0.3) Viper (0.3)	**XJ**	5series (0.3) Corvette (0.6)
GrandMarquis	**Efficient**	**XK**	Corvette (0.4) Sclass (0.5)
GrandPrix	**Efficient**	**Xtype**	5series (0.4) 7series (0.2) Corvette (0.2)
GS	5series (0.4) Accord (0.1) Sclass (0.4)	**Z3_Z4**	911Carrera (0.6) ClKclass (0.2)
Impala	**Efficient**		

Table 6: Output slacks in output-oriented model

Car-Model	Awareness	Attitude	Purchase Intention	Sale	Car-Model	Awareness	Attitude	Purchase Intention	Sale
3series	0.0%	0.0%	0.0%	0.0%	Impreza	36.8%	0.0%	327.3%	0.0%
300M	3.6%	0.0%	0.0%	0.0%	Ion	15.6%	0.0%	36.2%	0.0%
350Z	0.0%	0.0%	0.0%	40.6%	IS	17.3%	0.0%	286.4%	143.4%
40series	11.1%	0.0%	182.1%	43.8%	Jetta	0.0%	6.9%	69.1%	0.0%
5series	0.0%	0.0%	0.0%	0.0%	Lancer	0.0%	0.0%	0.0%	0.0%
60series	12.2%	0.0%	0.0%	0.0%	Legacy	0.0%	0.0%	0.0%	0.0%
7series	0.0%	0.0%	0.0%	0.0%	Lsseries	0.0%	0.0%	64.7%	0.0%
70series	12.5%	0.0%	221.1%	0.0%	M35_45	9.3%	0.0%	570.0%	338.8%
80series	5.0%	13.0%	0.0%	89.7%	Malibu	0.0%	20.2%	7.0%	0.0%
911Carrera	0.0%	0.0%	0.0%	0.0%	Maxima	0.0%	0.0%	0.0%	0.0%
93	18.2%	0.0%	257.1%	106.2%	Mazda6	11.6%	0.0%	58.8%	0.0%
95	0.0%	0.0%	324.3%	324.5%	MonteCarlo	0.0%	0.0%	0.0%	0.0%
A4	6.0%	0.0%	145.8%	0.0%	Mustang	0.0%	0.0%	0.0%	0.0%
A6	0.0%	0.0%	62.6%	60.4%	MX5Miata	0.0%	25.1%	57.9%	12.6%
A8	0.0%	0.0%	180.0%	192.6%	NewBeetle	0.0%	12.6%	32.2%	0.0%
Accent	0.0%	0.0%	0.0%	0.0%	Optima	0.0%	47.2%	430.2%	0.0%
Accord	0.0%	0.0%	0.0%	0.0%	Passat	0.0%	0.0%	179.2%	159.0%
Aerio	0.0%	0.0%	0.0%	0.0%	Prius	0.0%	0.0%	0.0%	0.0%
Altima	0.0%	0.0%	0.0%	0.0%	Ptcruiser	0.0%	0.0%	0.0%	0.0%
Avalon	3.7%	0.0%	0.0%	0.0%	Rio	0.0%	0.0%	0.0%	0.0%
Boxster	0.0%	0.0%	0.0%	77.5%	RL	7.5%	0.0%	255.3%	283.1%
Cclass	15.0%	0.0%	176.5%	19.9%	RSX	14.4%	0.0%	215.6%	0.0%
Camry	0.0%	0.0%	0.0%	0.0%	Sclass	0.0%	0.0%	0.0%	0.0%
Civic	0.0%	0.0%	0.0%	0.0%	S2000	0.0%	0.0%	0.0%	0.0%
Clclass	0.0%	0.0%	0.0%	0.0%	SC	0.0%	0.0%	0.0%	0.0%
CLKclass	0.0%	0.0%	0.0%	0.0%	Sebring	0.0%	7.2%	304.1%	0.0%
Corolla	0.0%	0.0%	0.0%	0.0%	Sentra	0.0%	0.0%	156.9%	0.0%
Corvette	0.0%	0.0%	0.0%	0.0%	Slclass	0.0%	0.0%	0.0%	0.0%
CTS	0.0%	0.0%	62.4%	0.0%	SLKclass	9.1%	0.0%	128.2%	97.9%
Eclass	0.0%	0.0%	0.0%	0.0%	Sonata	0.0%	76.3%	125.1%	0.0%
Eclipse	0.0%	35.1%	0.0%	17.8%	Taurus	0.0%	0.0%	0.0%	0.0%
Elantra	0.0%	0.0%	56.4%	0.0%	Tiburon	7.4%	67.4%	26.7%	0.0%
ES	16.1%	0.0%	82.5%	0.0%	TL	18.0%	0.0%	1.8%	0.0%
Focus	0.0%	39.1%	28.1%	0.0%	TownCar	0.0%	0.0%	0.0%	0.0%
Forenza	148.7%	191.0%	547.8%	0.0%	TSX	35.0%	0.0%	250.6%	0.0%
G35	17.7%	0.0%	107.0%	51.1%	Vibe	0.1%	0.0%	20.1%	0.0%
Galant	0.0%	40.5%	168.4%	0.0%	Viper	0.0%	0.0%	0.0%	0.0%
Golf_GTI	0.0%	7.1%	282.4%	0.0%	XJ	0.0%	0.0%	425.0%	367.3%
GrandMarquis	0.0%	0.0%	0.0%	0.0%	XK	0.0%	0.0%	669.8%	763.0%
GrandPrix	0.0%	0.0%	0.0%	0.0%	Xtype	0.0%	0.0%	260.9%	166.0%
GS	6.7%	0.0%	318.1%	280.8%	Z3_Z4	0.0%	0.0%	0.0%	17.0%
Impala	0.0%	0.0%	0.0%	0.0%	**Total**	3.6%	3.7%	31.6%	9.1%

Table 7 shows statistics of Kmeans-cluster analysis of car-models on two strategic dimensions of price and quality.

Table 7: Kmeans cluster analysis

Initial Cluster Centers			
		Cluster	
	1	2	3
Quality	3.67	2.33	3.83
Price	95,412	10,642	50,162
Iteration History			
		Cluster	
Iteration	1	2	3
1	4550	9409	5254
2	10530	801	805
3	4064	0	1902
4	2947	0	2035
5	0	801	1617
6	0	415	683
7	0	404	662
8	0	0	0
Final Cluster Centers			
		Cluster	
	1	2	3
Quality	4.13	3.33	4.08
Price	73,321	19,231	37,203
Distances between Final Cluster Centers			
Cluster	1	2	3
1		54090	36118
2	54090		17972
3	36118	17972	
Number of car-models in each Cluster			
Cluster	1	10	
	2	46	
	3	27	

Based on this clustering, our 93 car-models are classified in three distinct groups. Clusters centers well describe the strategy of each group. Cluster 1 has the highest level of quality and price, representing Porter's differentiation strategy. On the other hand, cluster 2, with the lowest level of quality and price, expresses a cost-leadership strategy. Cluster 3 has the medium level in both dimensions. Car-models in this cluster pursue a combination of both strategies, trying to deliver acceptable quality at an affordable price. Overall, 10 car-models are assigned to the differentiation cluster, 46 models to the cost-leadership cluster, and finally the remaining 27 car-models formed the combined cluster. Table 8 shows this group assignment.

Table 8: Strategic group assignment of car-models in U.S. market

Car-model	Cluster	Car-model	Cluster	Car-model	Cluster
Clclass	1	Galant	2	Lsseries	3
SC	1	NewBeetle	2	60series	3
7series	1	GrandMarquis	2	SLKclass	3
Sclass	1	Optima	2	IS	3
A8	1	93	2	Eclass	3
Slclass	1	Passat	2	G35	3
911Carrera	1	Ion	2	Boxster	3
Viper	1	Prius	2	RL	3
XK	1	Accord	2	GS	3
XJ	1	Ptcruiser	2	S2000	3
Impala	2	Camry	2	TL	3
Lancer	2	Rio	2	5series	3
Legacy	2	Elantra	2	TownCar	3
A4	2	RSX	2	CTS	3
Jetta	2	Golf_GTI	2	3series	3
300M	2	40series	2	Cclass	3
Accent	2	Impreza	2	ES	3
Malibu	2	Sebring	2	350Z	3
Aerio	2	Altima	2	70series	3
Maxima	2	Sentra	2	Corvette	3
Avalon	2	Forenza	2	95	3
Mazda6	2	Sonata	2	A6	3
Civic	2	Vibe	2	80series	3
MonteCarlo	2	Taurus	2	CLKclass	3
Eclipse	2	GrandPrix	2	Xtype	3
Mustang	2	Tiburon	2	M35_45	3
Focus	2	Corolla	2	Z3_Z4	3
MX5Miata	2	TSX	2		

Cluster 1 : Differentiation Strategy
Cluster 2: Cost-leadership Strategy
Cluster 3: Combined Strategy

Dispersion of car-models across two strategic dimensions of price and quality is illustrated in Figure 7.

Figure 7: Strategic clusters of car-models in U.S. market

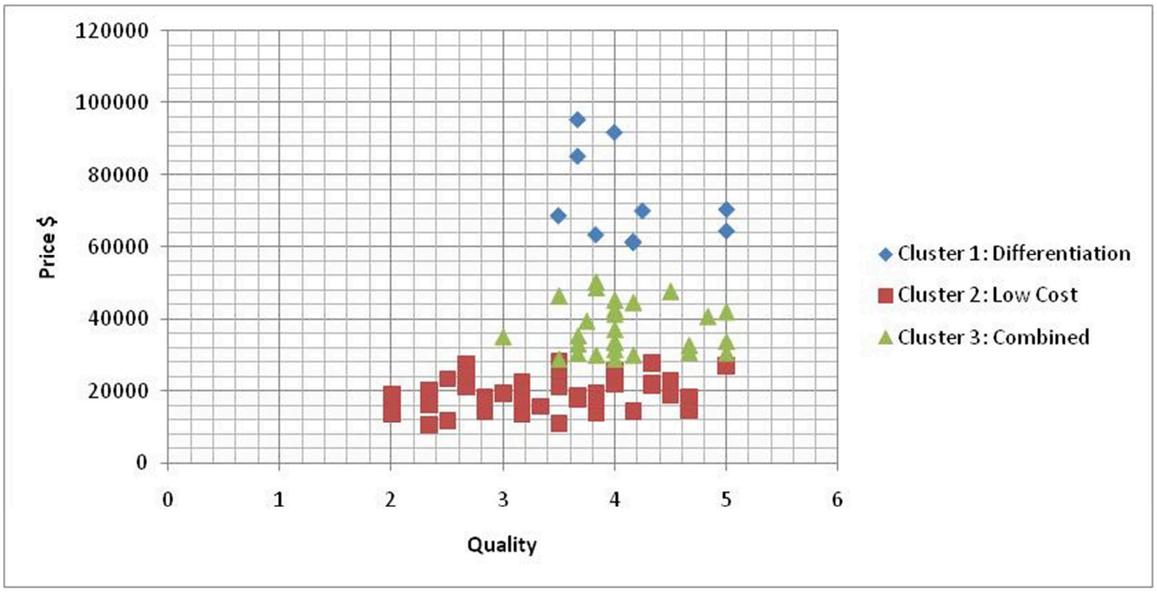


Table 9 illustrates the results of ANOVA for advertising expenditure of these clusters. In terms of overall advertising expenditure, ANOVA results reported a significant difference among three clusters ($p < 0.005$). Independent planned t-test showed advertising expenditure was significantly lower for differentiation cluster, and higher for cost-leadership strategy ($p < 0.005$) supporting our first hypothesis (H1). As predicted, the in cost-leadership cluster there is a higher degree of competition with lower level of differentiation among various car-models. Accordingly, advertising plays a critical role in influencing customers' decision making process. Moreover, since quality is significantly lower in this group of cars, advertising can be a practical tool for signaling the missing quality. However, for advertising to be efficient in signaling quality, a reasonable minimum level of quality is always necessary. It should be noted that in this study we compared total budget of advertising between clusters, and not relative advertising which shows the advertising budget per unit sold. Although differentiated car-models may advertise relatively more per unit comparing to cost-leadership car-models, but their total advertising budget on average, is only 15% of advertising budget in cost-leadership cluster. In terms of managerial perspectives this finding confirms the strong competitive advertising in cost-leadership cluster. This should be helpful for new comers or auto maker with a wide range of car-models that compete in different clusters, to be well aware of advertising intensity of different clusters.

Table 9: Differences in advertising expenditure

		Advertising Expenditure (000$)
Differentiation strategy		
	Mean	1,500
	(Variance)	(2,325,391)
Cost-leadership strategy		
	Mean	9,872
	(Variance)	(113,103,254)
Combined strategy		
	Mean	4,493
	(Variance)	(15,132,252)
ANOVA		
	F	6.18
	P-Value	0.003
Planned t-test		
	t	-5.10
	P-Value	0.000

ANOVA results for awareness reported in Table 10. Although ANOVA failed to find a significant difference between three clusters ($p > 0.1$), planned t-test revealed that differentiation car-models possess higher level of awareness comparing to low cost car-models ($p < 0.05$) leading to rejection of H2a. In terms of advertising inefficiency in producing awareness, ANOVA showed no significant difference between three clusters ($p > 0.1$), yet again planned t-test confirmed higher percentage of shortfalls in cost-leadership cluster and support H2b ($p < 0.05$). Overall, while cost-leadership and combined strategies show similar characteristics, differentiation strategy seems to be significantly different. On average low-cost car-models have to create about 7% more awareness to be efficient. In terms of managerial implication, findings may suggest low cost car-models to invest more in media with higher visibility and reach to overcome lack of awareness. For differentiation car-models since quality and word-of-mouth advertisements help to obtain the required level of awareness, advertising practices may focus on other aspects such as persuading potential customers to purchase.

Table 10: Differences in cognitive stage

	Awareness	%shortfalls
Differentiation strategy		
Mean	66.18	0.00%
(Variance)	(61.06)	(0.00)
Cost-leadership strategy		
Mean	58.48	6.79%
(Variance)	(369.21)	(0.05)
Combined strategy		
Mean	62.01	5.42%
(Variance)	(95.53)	(0.00)
ANOVA		
F	1.16	0.61
P-Value	0.318	0.548
Planned t-test		
t	2.05	-2.00
P-Value	0.024	0.026

Table 11 shows the differences between clusters in affective stage. As indicated in the table, there was a significant difference in positive attitude between three strategic groups ($p < 0.005$). Planned t-test confirmed higher level of positive attitude for differentiation cluster and lower level for cost-leadership strategy ($p < 0.005$) supporting our H3a. Car-models with differentiation strategy had the highest level of positive attitude, followed by combined strategy and cost-leadership, in that order. This was in line with previous researches that identified quality as a determinant of positive attitude toward car-models. Regarding the level of advertising inefficiency ANOVA found significant difference between all clusters ($p < 0.1$) and planned t-test confirmed higher level of shortfalls in positive attitude among cost-leadership cluster comparing to differentiation cluster ($p < 0.05$). As expected, for differentiation cluster, there was no shortfall in attitude (0.00%), while advertising is required to produce about 12.51% more positive attitude among low-cost car-models. In terms of managerial perspective, this may suggest low-cost car models to design their advertising contents in a way that signal the overlooked or missing quality to create higher positive attitude among audiences. In terms of media planning, cost-leadership car-models may invest more on media with higher level of emotional engagement. These car-models may be also better off by using affective advertising strategies rather than informative or comparative. Affective ads by invoking feelings and emotions of customers enhance the likability of car-model and ultimately increase the positive attitudes. Differentiated car-models on the other hand already receive high level of positive attitude. Accordingly, these car-models may use informative and comparative ads more frequently to distinguish themselves from similar counterparts and increase their behavioral variables such as purchase intention and sales volume.

Table 11: Differences in affective stage

	Attitude	%shortfalls
Differentiation strategy		
Mean	66.47	0.00%
(Variance)	(81.74)	(0.00)
Cost-leadership strategy		
Mean	45.57	12.51%
(Variance)	(310.83)	(0.11)
Combined strategy		
Mean	62.61	0.48%
(Variance)	(103.05)	(0.00)
ANOVA		
F	15.66	2.54
P-Value	0.000	0.085
Planned t-test		
t	5.41	-2.61
P-Value	0.000	0.006

Table 12 shows the differences between clusters in behavior stage. In terms of purchase intention ANOVA results revealed significant differences between all three clusters ($p < 0.005$). Planned comparison of cost-leadership and differentiation strategies confirmed higher level of purchase intention in cost-leadership cluster, supporting our hypothesis H4a ($p < 0.005$). The same results found for sales volume. These results shows cost-leadership car-models have competitive advantage over behavioral variables. In terms of advertising efficiency in creating purchase intention both ANOVA and t-test failed to show significant difference between clusters ($p > 0.1$) leading to rejection of H4b. A quick glance at the results reveals high percentage shortfalls in purchase intention of all car-models. Inefficient car-models in all three clusters have to increase purchase intention substantially to become efficient. This shows the diversity of car-models in each cluster regarding this variable. In all clusters there are examples of car-models with significantly high percentage of shortfalls in purchase intention and examples of fully efficient models in that regard. Car-models with significant low purchase intention can incorporate other marketing approaches such as price promotion that influence short-term behavioral variables more effectively. In terms of advertising efficiency in creating sales volume, ANOVA found significant differences between clusters ($p < 0.005$). Result of planned t-test in comparison of two dominant strategies confirmed that differentiation strategy experience higher level of advertising inefficiency in creating sales supporting hypothesis H5 ($p < 0.1$). In terms of managerial perspective, differentiated car-models that receive high level of awareness and attitude may be better off by using informative and comparative ads to increase their behavioral variables as much as possible.

Table 12: Differences in behavioral stage

	Purchase Intention	**%shortfalls**	**Sales Volume**	**%shortfalls**
Differentiation strategy				
Mean	0.07	127.48%	2,217	132.29%
(Variance)	(0.00)	(5.55)	(2,855,305)	(6.43)
Cost-leadership strategy				
Mean	0.63	86.20%	26,232	7.38%
(Variance)	(0.55)	(1.72)	(601,762,171)	(0.08)
Combined strategy				
Mean	0.24	108.21%	8,486	73.73%
(Variance)	(0.04)	(2.14)	(44,289,279)	(1.2)
ANOVA				
F	6.44	0.39	11.38	7.05
P-Value	0.003	0.677	0.000	0.002
Planned t-test				
t	-5.07	0.54	-6.57	1.56
P-Value	0.000	0.30165545	0.000	0.077

Overall, regarding different effects of advertising, car-models with differentiation strategy found to be better at initial stages of purchase funnel thanks to the element of quality, while car-models with cost-leadership strategy outperform at terminal stages because of the element of price. However, as indicated in table 14, high advertising efficiency is not limited to a specific group, and there were examples of car-models with different strategies that recognized as efficient advertisers, with respect to their level of advertising budgets and advertising effects. As reported in the Table 14, ANOVA found no significant difference among advertising efficiency scores of three clusters ($p > 0.1$). However, planned t-test in comparison of differentiation strategy and cost-leadership showed that differentiation strategy possesses higher efficiency score ($p < 0.05$). This group of car-models with lower aggregate advertising budgets creates relatively higher advertising outputs. As emphasized before, cost-leadership car-models have to apply media and advertising planning techniques to increase the effectiveness of advertising practices, especially at affective and cognitive stages. Automakers with wide range of product categories, such as Audi that has car-models in different cluster of differentiation (e.g. A8 model) and cost-leadership (e.g. A4 model) should be aware of these differences and make advertising strategies accordingly. Overall, in this section I compared the effects of advertising across different strategic clusters. This can be helpful for newcomers and wide-range automakers to obtain more insights about differences in various strategic clusters. Moreover, the results of this section also provided insights regarding inefficiency of advertising in producing each communication effect in each different strategic cluster. Thus, managers and media planners of each inefficient car-model should utilize different advertising techniques based on their business strategies (differentiation vs. cost-leadership) to improve their advertising efficiency.

Table 13: Differences in advertising efficiency

	Efficiency Score	Efficient Models
Differentiation strategy Mean (Variance)	 92.78% (0.01)	Clclass, SC, 7series, Sclass, Slclass, 911Carrera, Viper
Cost-leadership strategy Mean (Variance)	 84.82% (0.03)	Impala, Lancer, Legacy, Accent, Aerio, Civic, Montecarlo, Mustang, GrandMarquis, Pruis, Accord, Ptcruiser, Camry, Rio, Altima, Taurus, GrandPrix, Corolla
Combined strategy Mean (Variance)	 88.98% (0.01)	Eclass, S2000, 5series, Towncar, 3series, Corvette, ClKclass
ANOVA F P-Value	 1.62 0.204	
Planned t-test t P-Value	 1.79 0.045	

Conclusion

Theoretical Implication

In this thesis I applied data envelopment analysis to benchmark advertising efficiency of car-models in U.S. car market. Benchmarking is a quite recent established tool that has drawn wide attention of scholars and practitioners in various disciplines including marketing. Data envelopment analysis is a new frontier method that has developed for benchmarking purposes. DEA can evaluate relative efficiency of firms by incorporating various numbers of inputs and outputs at once. Since DEA is a non-parametric approach it does not require imposition of any function relating inputs and outputs, and thus can be advantageous in cases with complex and/or unclear relations between inputs and outputs, and also when the relative importance of inputs and outputs are not clear. This makes DEA a perfect tool for analyzing efficiency in advertising context. There are many debates in terms of causal relationship between various outputs of advertising (cognition, affection, behavior), while the effect of advertising expenditure on these outputs is yet under question. Application of DEA enabled us to benchmark advertising efficiency of various car-models without making any assumptions in that regard. Recently, many studies applied DEA to benchmark advertising practices, by focusing on communicational effects of advertising or sales effects as outputs. However, this research went further by looking at the whole purchase funnel, and incorporating both communication and sales effects. Moreover, unlike most of advertising budgeting studies in automobile industry that focus on efficiency of advertising at brand-level (e.g. BMW versus Jaguar), this paper concentrates on those effects at product-level (3series versus XJ). This study performs a comprehensive research on both input (budgeting) and output (advertising effects) sides of advertising.

This thesis is composed of two studies with two distinct objectives. The first study focused on budgeting and the media-side of advertising at a macro-level, and input-oriented BCC model of DEA is applied in that regard. In total, our results reported 2.1% of over-advertising at model-level in U.S. car market, for the time period of 2002-2008. Generally, most of over-advertising occurred in broadcast and print media. This was not surprising since most of the advertising budget had being allocated there. However, they were recognized as the most efficient media with the lowest percentage rate of over-expenditure relative to their budgets (%slack). Overall, outdoor media was recognized as the most inefficient channel of advertising for car-models. In 2008, internet was the most inefficient media with the highest percentage of over-advertising. This seems to be the point that internet advertising became a prevalent marketing practice in U.S. car-market, and as a result of this sudden huge investment, its efficiency decreased dramatically. These results are slightly different with the results of advertising efficiency of Spanish car-market by Pergelova (2010) which conducted over the same time period. In that study Pergelova found internet as the most efficient media in advertising of automobile industry. This may imply existence of geographical and cultural differences in media efficiency within the same industry.

In the second study, I benchmarked advertising efficiency of car-models in U.S. car market in a three-year period, looking for more details. With focus on advertising effects, I applied output-oriented DEA model of DEA. Based on results, 39% of car-models under study found to be efficient advertisers in time period of 2004-2006. Thereafter, I investigated the influence of strategy on advertising practices. Price and quality were used as dimensions of strategy, to assign car-models into three cluster of differentiation, cost-leadership and combined strategies. The results revealed significant differences between advertising effects and efficiency of different strategic groups. Differentiated car-models showed higher level of positive attitude, while car-models with cost-differentiation strategy had higher level of purchase intention and sales volume. In terms of advertising inefficiency I found significant differences between different strategies. Overall, for differentiated car-models most of advertising inefficiency was related to behavior stage, while low-cost cars were inefficient more likely in affective stage.

Managerial Implication

In terms of managerial implications, DEA provides marketing managers and media planners with many insights and directions regarding advertising practices. Firstly, it helps them to evaluate the advertising efficiency, with inclusion of multiple inputs and outputs. This is a very important issue, since adverting has multiple levels of effects that are co-related; while exclusion of each may lead to falsified results and inclusion of all may be too complicated and challenging for using other methodology. Secondly, results of peer analysis of DEA, helps them to identify best practices in the industry for benchmarking, those that are most similar to them in terms of scope of advertising resources and outputs. Moreover, slack analysis of results provides further guidelines for managers, to identify inefficient media and modify and/or reallocate their advertising budgets. In general, other existing benchmarking methodologies do not provide such clear a guideline and easy steps for managers to follow, and DEA seems to be the most preferred benchmarking tool. Another advantage of DEA in terms of managerial implication is that it can be utilized for different strategic purposes of resource minimization or output maximization. This is an important issue since firms use advertising benchmarking for various reasons, sometimes to squeeze their budgets and sometimes to expand their outputs as much as possible, based on economic conditions, product life cycles, and many other macro-level factors.

Results of our first study indicates there is downward trend in both advertising budget and advertising efficiency of car-models at model-level and this should urge managers to use their advertising budget more efficiently. In terms of media, a noticeable portion of advertising budgets seems to be shifted from broadcast and print media to internet. A couple of issues need to be addresses here. First, for car-models that have not utilized internet advertising yet, this maybe be a critical point to consider this media as an effective tool. The results of this study provided the level of over-expenditure in each media for inefficient car-models. These over-spent advertising budgets can be reallocated in other media such as internet, to obtain better advertising outcomes. However, firms should not make unrealistic assumption regarding the effectiveness of this media and over-advertise there. Our results also indicate that in 2008, internet had the highest percentage of over-expenditure. Based on the results, in U.S. car market, broadcast and print are the most efficient media while outdoor and B2B found to be less efficient. This should urge managers and media planners to use these media more cautiously and effectively.

In the second study we identified differences in advertising effects and efficiency of car models with different strategies. Prior knowledge about these differences would help newcomers and automakers with wide-range of car-models and strategic positions, to better make advertising decisions. Overall, most of the inefficiency of differentiated car-models occurs in behavioral stage while cost-leadership car-models were mostly inefficient in producing cognitive and affective effects. This can help managers in advertising decision making process such as selection of media, contents and/or design of advertisements. For instance low-cost car-models should most rely on media with higher level of visibility and reach to create required level of awareness and also media with higher level of emotional engagement to create required level of positive attitude. In terms of advertising contents, these car-models may be better off by using affective advertising strategies rather than informative or comparative. Affective ads by invoking feelings and emotions of customers enhance the likability of car-model and ultimately increase the positive attitudes. Differentiated car-models on the other hand already receive high level of positive attitude. Accordingly, these car-models may use informative and comparative ads more frequently to distinguish themselves from similar counterparts and increase their behavioral variables such as purchase intention and sales volume.

Limitation and Future Researches

In terms of limitations, there are a couple of issues need to be addressed. Generally, two set of limitations are indentified in this study. First set of limitation goes back to DEA methodology, while the second set of limitation related to the research design per se. Since DEA is a deterministic approach, there is no room for errors and fit statistics to test the model. DEA incorporates noise as a part of inefficiency. Moreover, DEA as a non-parametric approach does not make any assumption and conclusion regarding the functional relationships between input and output variables. Accordingly, DEA is more used as an observatory rather than explanatory tool. For instance DEA does not explain the underlying reason behind low inefficiency of outdoor media in study 1 or low inefficiency of specific car-models in study 2 and further explanatory studies are required. Future researches, can utilize other frontier approaches such as parametric stochastic frontier analysis, for more conclusive results. Additionally, DEA results are very sensitive to outliers, and selection of inputs and outputs. In this research, best possible efforts made to omit outliers from our selection of car-models. Also I tried to have the most comprehensive selection of inputs and outputs possible. Finally, DEA evaluate and compare efficiency of DMU, based on unique different input and output-weights for each car-model, weights that are as favorable as possible to the DMU being evaluated. Although this can be noted as an advantage of DEA approach, it can be problematic in some cases. The underlying assumption here is that there is high ambiguity and no priori judgment about the relative value of inputs and outputs (baker, 2011). This issue can be justified in our model of advertising efficiency. Although increasing sales is the ultimate goal of advertising practices, it is very difficult if not impossible, without achieving some level of awareness and/or positive attitude among potential buyers. Since there is no agreed-upon theory regarding the relative importance of these outputs, DEA can be an appropriate tool in this setting.

The other set of limitations goes back to the research itself and its design as a descriptive observational study. Overall, advertising benchmarking is only one way of determining optimal level of advertising. One critical criticism to this approach is the fact that it assumes all units under evaluation are in the same situation. Among different methods of benchmarking DEA is relatively better in this regard, as it suggests separate unique optimization for each unit under study in terms of utilization of its budget to produce desired outputs. Nevertheless, benchmarking results should be compared with results of other theoretical approaches for more clarification and validity. Although the focus of this research has been solely on advertising, advertising outputs -awareness, positive attitude, purchase intention and specifically sales volume- could be affected by other marketing practices such as promotions. Additionally, those outputs can also be affected by corporate-level advertising (e.g. BMW) and/or dealership advertising. Future studies should be replicated by inclusion of these variables as control variables. Moreover, since the data is gathered for U.S. car-market, the efficiency results cannot be generalized for same car-models in other regions. Additionally, the results regarding differences of advertising effects on products with different strategies, may not be applicable to other product categories, and further studies can be conducted in that direction. Moreover, in this research we did not distinguish between different segments of cars such as sedan, sport cars, economy or luxury class. Future study can benchmark advertising efficiency of each segment separately.

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