Leading advertisers efficiency evaluated by data envelopment analysis *

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Abstract. In this paper we analyze the problem of measuring the advertising efficiency of the Leading US Advertisers during the period 2001-2006. We use the DEA (Data Envelopment Analysis) approach that enables to evaluate the relative efficiency in case of multiple inputs and outputs. In particular, the classical CCR-DEA model is first implemented in each year considered; a windows analysis approach is then used in order to better capture the dynamics of efficiency. Finally, the effect on efficiency of advertising spending over time, is captured by Adstock as an additional variable of the DEA model. The dynamics of Adstock is described by a finite difference equation.

Keywords: Advertising, Efficiency, Data envelopment analysis, Adstock.

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1 Introduction

In this paper we focus on the problem of measuring advertising spending efficiency.

This is an important marketing issue that recently has been discussed by using a Data Envelopment Analysis (DEA) approach.

The DEA methodology represents a nonparametric method of measuring the efficiency of similar entities. Since the original contribution of Charnes et al. (1978), the DEA approach has been extensively adopted in management science. DEA can be considered as a tool at the disposal of marketing researchers, as noted by Charnes et al. (1985), who first discussed the potential applications of DEA in marketing science. Recently Luo (2004) emphasized the relevant implications of DEA for marketing research in the area of consumer, managerial and marketing models. Marketing issues that have been treated by employing DEA are the evaluation of the efficiency of retailing and selling function (Donthu et al. 1998; Thomas et al. 1998; Mahajan. Jayashree 1991), or the assessment of the performance of a supply chain system (Zhu 2003).

Recent papers address the problem of measuring the efficiency of advertising. More precisely, Luo and Donthu (Luo, Donthu 2001; Luo, Donthu 2005) apply DEA and Stochastic Frontier Technique to determine the efficient advertisers among the top 100 U.S. advertisers in 1997 and 1998, whereas Färe et al. (2004) use DEA techniques to estimate the overall cost efficiency in advertising and the optimal mix of advertising media considering a set of firms of the same industry (beer industry, namely) during the decade 1983-1993.

In this paper we will study the evolution of advertising spending efficiency concerning 70 leading U.S. advertisers from 2001 to 2006. Data are collected from the yearly Advertising Age reports on U.S. Leading National Advertisers (http://adage.com/). Efficiency is computed first via a classical DEA model and then by using windows analysis to better capture the efficiency evolution over time. In order to take into account the dynamic effect of cumulated advertising spending on efficiency, we then consider the yearly AdStock (Broadbent 1979) as an additional variable of the DEA model. AdStock, whose evolution is described by a finite difference equation, captures the cumulative building of an advertising capital stock.

The paper is organized as follows: in Section 2 we analyze the Leading US advertisers applying the classical CCR-DEA model in each year of the period 2001-2006, while we perform a DEA window analysis in Section 3. AdStock is introduced as an additional output in Section 4, where the corresponding efficiency results are discussed. Some final remarks are given in Section 5.

2 Leading US advertisers efficiency with the CCR-DEA model

In this section, we use the CCR-DEA approach in order to measure the efficiency of the leading US advertisers from 2001 to 2006.

Data were obtained from the Advertising Age reports (http://adage.com/), which select the 100 top US advertisers considering their advertising spending on different media.

Data Envelopment Analysis (DEA) is a well established optimization based technique which allows to measure and compare the performance of decision making units [2].

In the DEA literature the decision making units can be firms, nonprofit institutions, health services, universities, and so on. In the advertising efficiency models the decision making units (DMUs) are the advertisers whose performance have to be evaluated.

The DMUs may be viewed as firms that use different inputs and produce different outputs. In a multi-input multi-output framework the efficiency of a given DMU can be computed as the ratio of weighted outputs to weighted inputs.

The computation of a weighted ratio requires a set of weights to be defined; the DEA's idea is to define the efficiency measure by assigning to each DMU the most favorable weights, which are computed by maximizing the efficiency ratio of the DMU considered. Formally, consider a set of n DMUs (advertisers) to be evaluated and let us suppose that each advertiser has at its disposal m different media (newspapers, television, etc.); denote by

y_{rj}^{τ}	the amount of output r for unit j, at time τ
x_{ij}^{τ}	the amount spent by unit j in media i (the inputs) at time τ

For each time τ and for each target unit j_0 we consider the following CCR DEA problem, that allows to compute the efficiency score for unit j_0 [5]:

$$\max_{\{u_r^{\tau}, v_i^{\tau}\}} \quad \frac{\sum_{r=1}^{s} u_r^{\tau} y_{rj_0}^{\tau}}{\sum_{i=1}^{m} v_i^{\tau} x_{ij_0}^{\tau}} \tag{1}$$

subject to

$$\frac{\sum_{r=1}^{s} u_r^{\tau} y_{rj}^{\tau}}{\sum_{i=1}^{m} v_i^{\tau} x_{ij}^{\tau}} \leq 1 \qquad j = 1, 2, \ldots, n \tag{2}$$

$$u_r^{\tau} \geq \varepsilon \qquad r = 1, 2, \ldots, s \tag{3}$$

$$v_i^{\tau} \geq \varepsilon \qquad i = 1, 2, \ldots, m \tag{4}$$

where

u_r^{τ}	is the weight assigned to the output y_{rj}^{τ} $(r = 1, 2, ..., s)$
v_i^{τ}	is the weight assigned to the input x_{ij}^{τ} $(i = 1, 2, ..., m)$
$\varepsilon > 0$	is a non-Archimedean infinitesimal.

The optimal objective function value represents the efficiency measure assigned to the target DMU j_0. An efficiency measure less than 1 characterizes the inefficient units: also with the most favorable weights, these DMUs are dominated by the other ones. DMUs with efficiency 1 are called (technically) efficient.

In the efficiency analysis of US Leading Advertisers, we consider four input variables: paper advertising spending (which aggregates Magazines and Newspapers ad spending), broadcast advertising spending (which aggregates TV and Radio ad spending), internet advertising spending and unmeasured advertising spending. Unmeasured spending is an Ad Age estimate and includes direct mail, sales promotion, catalogs, farm publications and special events, to name a few. Unmeasured spending basically is the difference between a company's reported or estimated ad costs and its measured spending on different media. As output variable we consider the corresponding sales of the advertiser in the same year.

The DEA efficiency analysis has been undertaken for τ ranging from 2001 to 2006. Due to data availability in the period 2001-2006, 70 advertisers were selected among the 100-top advertisers.

Table 1 summarizes the DEA analysis results. We report mean and lower efficiency scores and the number of relatively efficient advertisers for each year.

	2001	2002	2003	2004	2005	2006
mean efficiency score	0.294	0.253	0.313	0.340	0.329	0.302
lower efficiency score	0.045	0.047	0.051	0.065	0.044	0.049
number of efficient advertisers	4	3	5	8	5	4

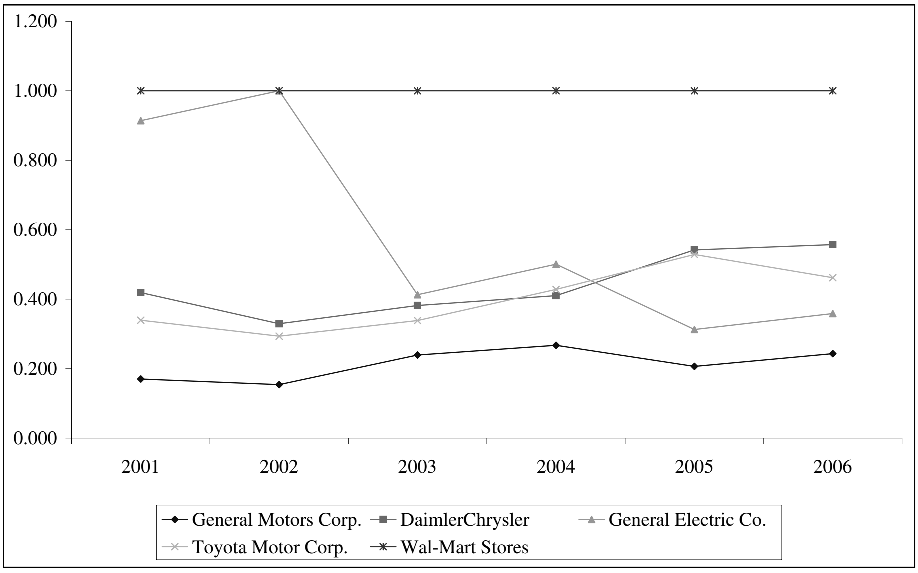
Table 1: Summary of the results of the CCR-DEA analysis, 2001-2006.

Figure 1 represents the efficiency scores dynamics of the five advertisers which have, respectively, the highest and lowest sales in 2006. Figure 2, instead, represents the efficiency scores of the five advertisers with, respectively, highest and lowest advertising costs in 2006.

The relative efficiency scores of a single advertiser are influenced by changes in total sales, advertising policies of the advertiser itself and also of the other advertisers in the comparison set. Relevant efficiency score changes may also be due to company merging.

For example, considering the General Electric Co. efficiency scores in Figure 1, we can note that its efficiency score is 1 in 2002 and it results to be remarkably lowered starting from 2003. This is essentially due to a couple of reasons. On one hand G.E. in 2003 decided an aggressive campaign, to be supported with more than $100 millions in television, print and online advertising thus implying a big rise of advertising costs but the corresponding rising of sales was less than proportional. On the other hand in 2004 G.E. bought Vivendi's television and movie assets, the new company being named NBC Universal. The data on advertising spending in 2003 are obtained by aggregating the corresponding data of the two companies.

As another example, in Figure 2 we can observe some remarkable changes in AT&T's advertising efficiency scores. AT&T is in fact the name of the merged SBC Communications and AT&T Corp. The merging was completed at the end of 2005, AT&T became the surviving name. From 2001 to 2004 advertising spending and sales of the former AT&T Corp. decreased, with a higher decreasing rate for advertising. This fact contributes to an increase of advertising efficiency score for AT&T during that period. After that, due to a big rise of advertising in the merged company, and less than proportional rising of sales, the relative efficiency score of AT&T diminishes strongly.



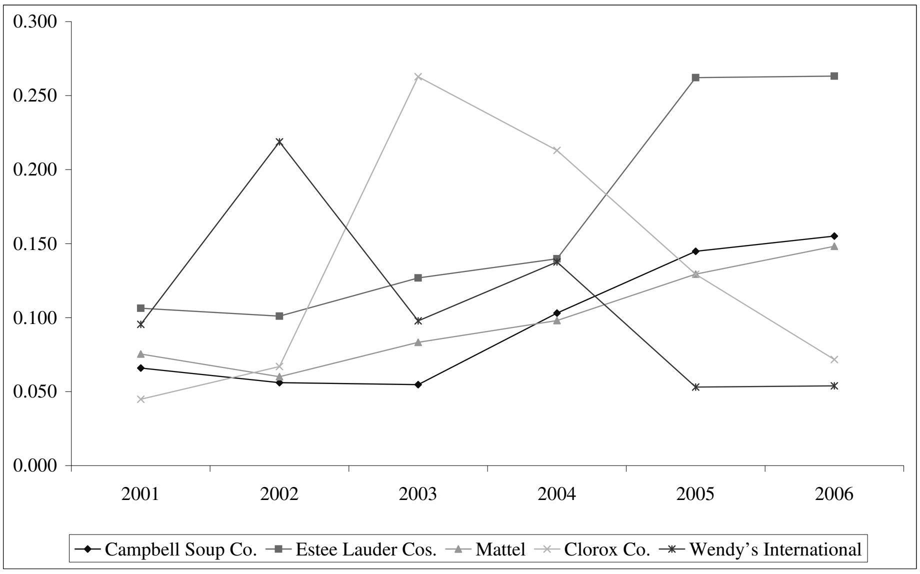
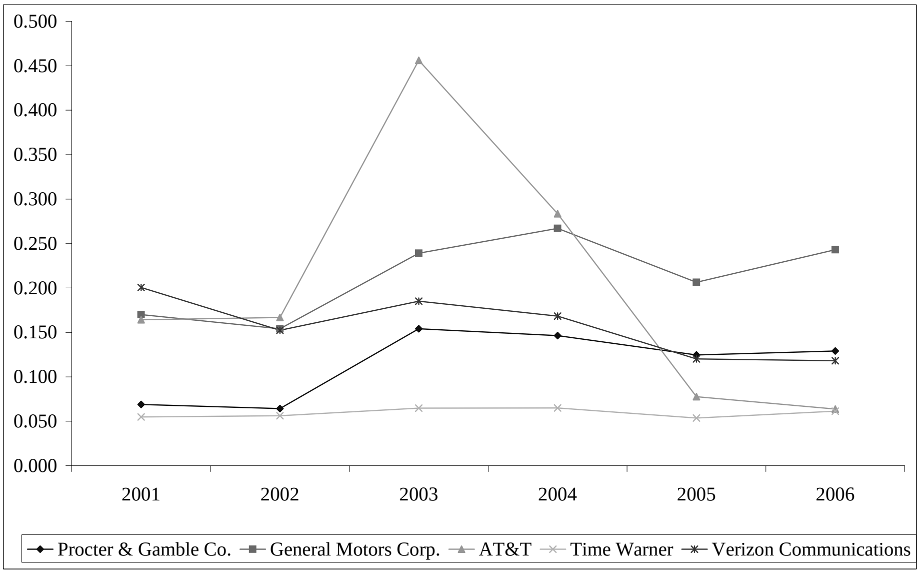


Figure 1: Efficiency scores of the five advertisers with highest and lowest sales, respectively.



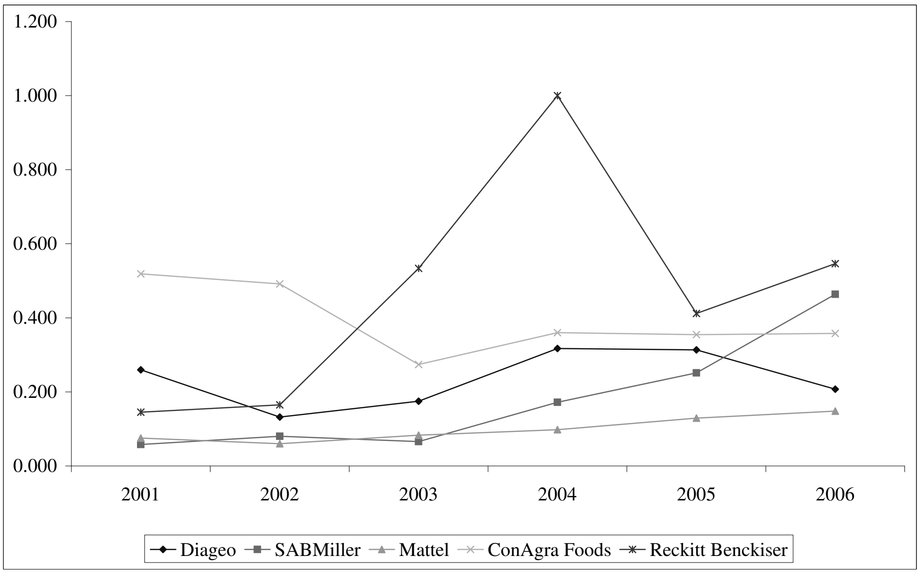


Figure 2: Efficiency scores of the five advertisers with highest and lowest advertising costs, respectively.

3 A Window Analysis approach for dynamic advertising

In the traditional static DEA models the efficiency results are computed in a defined time of evaluation; the inputs and the outputs are observed in a specific point of time; the models assume that the outputs produced in a given time period are caused only by the inputs observed in the same period.

One simple approach that allows to take into consideration various time periods together, is the window analysis. The approach consists in forming time windows of p periods and solving DEA problems associated to each window.

The feature is that in each window the decision making units observed in different time periods are considered as different units and this allows to compare the efficiency of various units in each given time period, but also to evaluate the change of the efficiency score of each target unit over time. Evaluating the efficiency of n decision making units with windows of p years (or p months), entails a total of np observations in each time window.

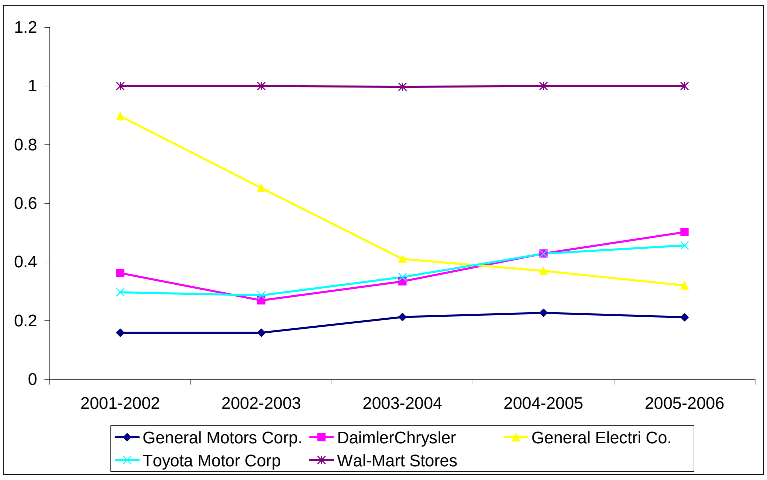
We considered two-years windows ($p = 2$). The procedure therefore consists in performing the efficiency analysis starting from the window 2001-2002 considering 140 ($= 70 \times 2$) advertisers in the years 2001 and 2002; then the window is shifted of one year by considering the period 2002-2003 and the DEA analysis is performed again; the process continues up to the final window 2005-2006.

The results of the window analysis may by organized in a table; for example Table 2 represents the efficiency results for advertiser DaimlerChrysler. The column view indicates the stability of the results across the different data sets (*average by term*), whereas the row view determines the trends with the same data set (*average through window*).

	2001	2002	2003	2004	2005	2006	average through window
	0.417	0.307					0.362
DaimlerChrysler		0.321	0.217				0.269
			0.365	0.302			0.334
				0.409	0.449		0.429
					0.542	0.462	0.502
average by term	0.417	0.314	0.291	0.356	0.495	0.462	

Table 2: An example of window analysis results for DaimlerChrysler advertiser.

Figure 3 illustrates the average through window for the five advertisers with the highest sales and for those ones with the highest advertising costs, by considering a window spanning over two years; Figure 4 illustrates the average by term for the five advertisers with the highest sales and for those ones with the highest advertising costs.



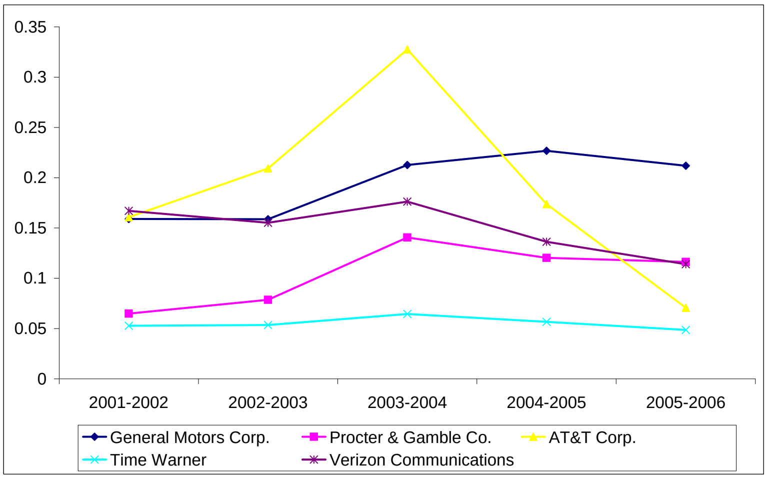


Figure 3: Averages through window of the five advertisers with highest sales and highest advertising costs, respectively.

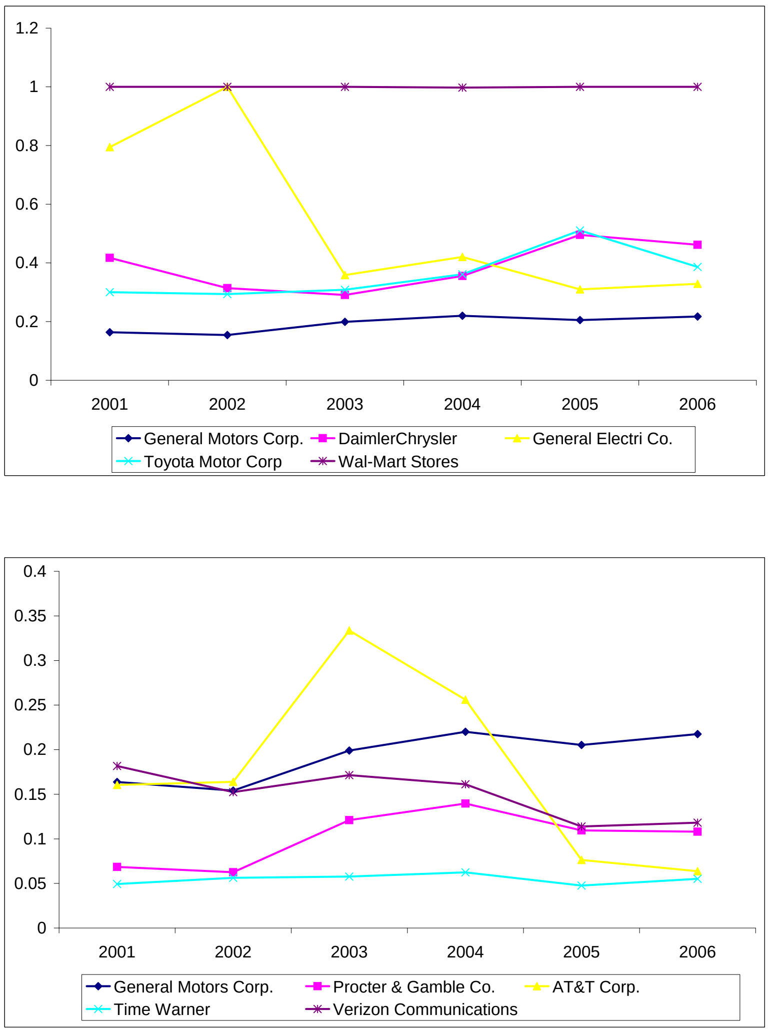


Figure 4: Averages by term of the five advertisers with highest sales and highest advertising costs, respectively.

4 Advertising efficiency in presence of AdStock

Finally we undertake an analysis of the efficiency of the Leading US Advertisers, by examining the effect on the efficiency scores of considering past advertising expenses as a proxy for the AdStock variable.

Advertising AdStock is a term introduced by Broadbent (1979) to describe the lagged effect of advertising on sales, i.e. an higher advertising expenditure today may cause an higher level of sales in the future (advertising carry-over effect).

Actually, it is usually assumed that current advertising may affect not only current product demand, but also future demand. The repeated exposure to advertising builds awareness in consumer markets (AdStock), resulting in future sales.

The efficiency of an advertiser should therefore be measured considering his advertising expenditures *over time* and should also take into account the *depreciation* of the AdStock. We consider the basic AdStock dynamic (Broadbent, 1979):

$$AS_{n+1} = K_n + \lambda AS_n \tag{5}$$

where AS_n represents the AdStock at time n, $K_n \geq 0$ denotes the advertising exposures during year n and $\lambda \in [0, 1]$ represents the depreciation of cumulated effects of past advertising expenditure on sales.

We will assume the same value of λ for each advertisers, i.e. the market forgets in the same way all messages. This rather restrictive assumption, can be justified considering the fact that the business of leading advertisers usually covers rather different sectors and λ could represent a sort of "over-sectorial" depreciation effect. In our simulation we consider $\lambda = 0.5$, i.e. the halving time is exactly one year.

In order to provide a possible way to compute an initial value for the stock of advertising-goodwill we have assumed that the mean value of the advertising stock in the market (70 advertisers) is proportional to the mean value of the sales in the market in the same year n:

$$\text{mean value of AdStock}(n) = \alpha \ \cdot \text{mean value of sales}(n)$$

The value of α depends on the values of λ and is computed so as to minimize the variance of

$$\frac{\text{mean value of AdStock}(n)}{\text{mean value of sales}(n)}$$

in the considered time period.

We then compute the initial AdStock of each single advertiser in 2001, by multiplying its sales in year 2001 by α:

$$\text{AdStock}(i, 2001) = \alpha \cdot \text{sales}(i, 2001)$$

Since an higher AdStock today might allow higher sales in the future, we have performed an efficiency analysis of the Leading US Advertisers in the period 2001-2006, by considering the AdStock as an additional output of the DEA model.

Table 3 summarizes the DEA analysis results, with AdStock as an output. We report mean and lower efficiency scores and the number of relatively efficient advertisers for each year. With respect to the static DEA analysis (without AdStock), we note that including the AdStock variable causes a rise of the efficiency scores for all the advertisers and thus an increase of the mean scores and of the number of efficient units: this is the effect of adding one variable in a DEA model.

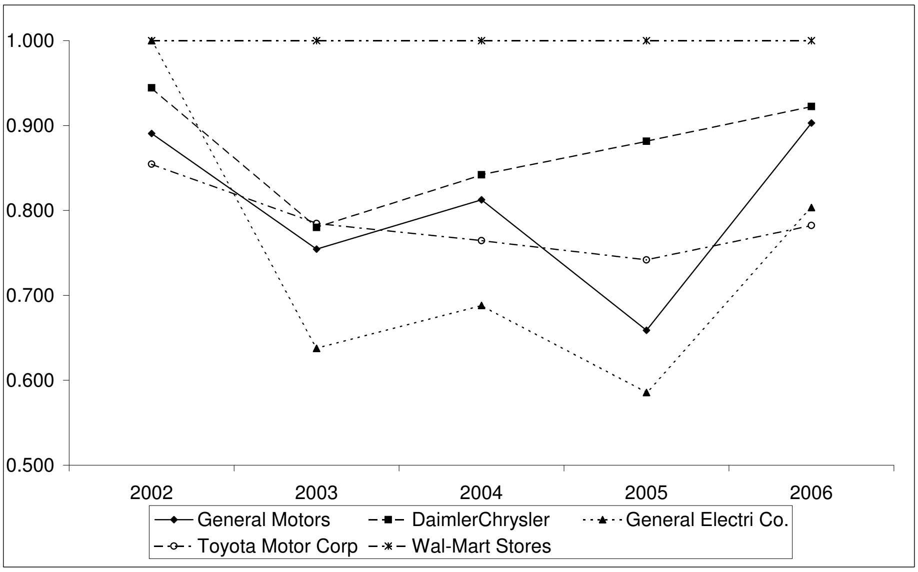
	2001	2002	2003	2004	2005	2006
mean efficiency score	0.978	0.933	0.861	0.854	0.791	0.881
lower efficiency score	0.943	0.768	0.638	0.577	0.355	0.622
number of efficient advertisers	22	20	17	18	17	20

Table 3: Summary of the results of the DEA analysis with AdStock, 2001-2006.

Moreover, adding AdStock may cause higher increases in the efficiency scores of those companies which have devoted many financial resources to advertising activities in the past and these expenses are viewed as a mean to increase future sales.

For example, let us consider General Motors and General Electric Co. and compare their efficiency scores computed by using the model with AdStock, with those obtained in the DEA static analysis without AdStock.

General Motors is both one of the five companies with highest sales and one of the five companies with highest advertising costs. Considering General Motors in 2005 and 2006 we note that, by using both models (with and without AdStock), the efficiency scores increase; remarkably, the efficiency's increase from 2005 to 2006 is much more relevant when we consider AdStock as an output; this is due to the cumulated effect of advertising activity. In effect, with the AdStock model, the dynamic effects of advertising are taken into account, and the influence of AdStock on sales is witnessed also by the sharp increase of the total sales of General Motors. This dynamic behavior can be emphasized by comparing the efficiency scores of General Motors with those obtained by General Electric Co., which is one of the five advertisers with highest sales. Also General Electric Co. displays an increase in sales from 2005 to 2006; however, this seems to be due to a less relevant AdStock accumulation during the considered time period. In fact, General Motors almost always outperforms General Electric Co., when we consider the model with Adstock, whereas we can observe substantially the opposite situation in the absence of AdStock (see Figures 1 and 5).



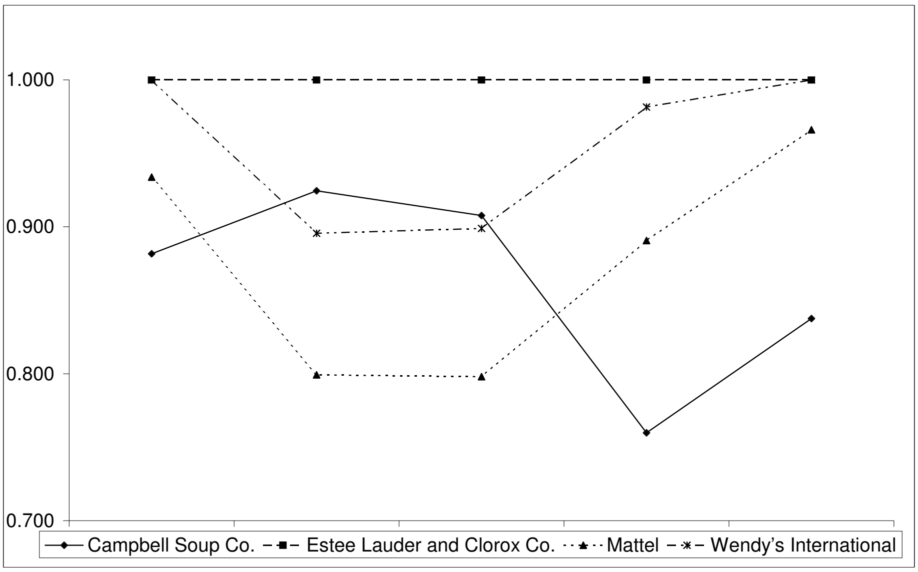


Figure 5: Efficiency scores, with AdStock, of the five advertisers with highest and lowest sales, respectively.

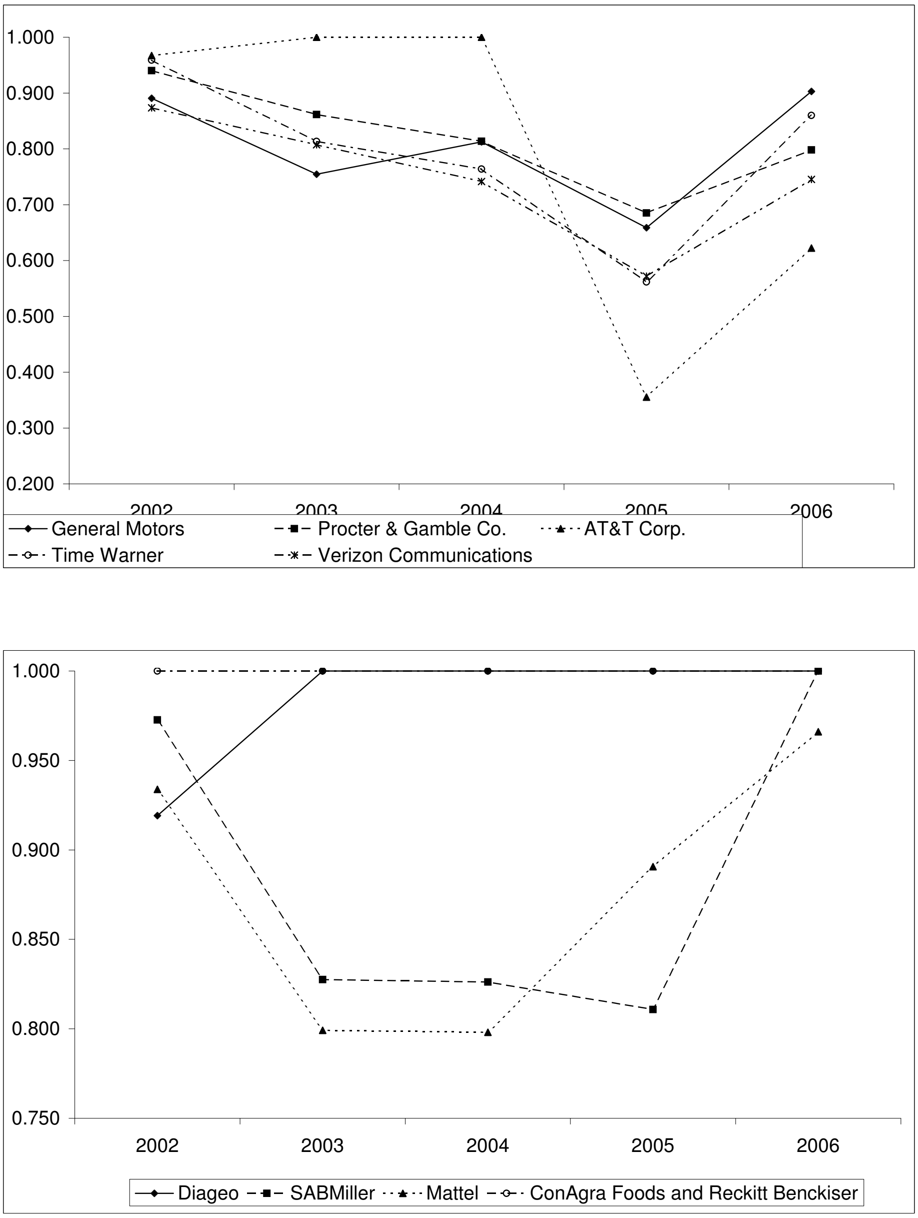


Figure 6: Efficiency scores, with AdStock, of the five advertisers with highest and lowest advertising costs, respectively.

5 Concluding remarks

In this paper we use both a static DEA approach and a Windows analysis in order to evaluate the efficiency of leading US advertisers from 2001 to 2006.

In order to take into account the effect of AdStock, we compute the efficiency scores by considering as additional inputs the past advertising expenditure, considered as a proxy of the advertising capital stock.

In static DEA models the efficiency scores are computed for single time periods and even if we implement the traditional (static) DEA model for each single time period we are not able to evaluate the improvement or the deterioration of the efficiency over time. On the other hand, the Windows analysis solves this problem only partially. In the literature one can find various attempts to extend the DEA methodology in a dynamic framework.

Introducing AdStock as an additional variable of the model may be considered as a step toward a dynamic framework. Our purpose in future is to formulate a dynamical DEA model which allows to estimate advertiser's "path efficiency" making use of the AdStock dynamics described by formula (5).

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