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Advertising Spending Efficiency Among Top U. S. Advertisers from 1985 to 2012: Overspending or Smart Managing?

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The current study tests two competing predictions of long-term adspend efficiency: the "overspending perspective" predicts continued high inefficiency, while the "smart manager perspective" predicts improved efficiency. Longitudinal analysis of efficiency among top 100 U.S. advertisers from 1985 to 2012 using data envelopment analysis reveals that inefficiency has increased over time. Approximately 61% of top advertisers are inefficiently using their ad dollars and are overspending by an average of 34%. Findings also indicate that the Internet, a medium highly praised and utilized for the amount and depth of consumer data it generates, has not impacted overall efficiency in any meaningful way.

Advertising spending efficiency (ASE) is of great interest and concern to marketers, ad agencies, and media companies due to ever-increasing media space/time costs and because it is a key component of return on investment (ROI) assessments (Ambler 2000; Sheth and Sisodia 2002). Inefficient advertising spending also contributes to lower profit margins and sales loss (Luo and Donthu 2005). The inefficiency of advertising and its negative impact is not new knowledge; marketers are aware that their advertising spending might not be as efficient as they hypothesize or hope (Aaker and Carman 1982; MacNiven 1980; Simon and Arndt 1980). Reviewing 60 empirical analyses of advertising spending, Aaker and Carman (1982) showed that a substantial amount of advertising inefficiency exists among the top U.S. advertisers and that many firms overadvertise. Overadvertising implies that advertisers could use less advertising spending to yield the same level of sales or generate more sales given the same adspend.

Certainly the concern over ASE is ongoing and becoming increasingly important as clients push for greater accountability from their marketing units and advertising agencies. However, little is known as to how advertising efficiency has changed, particularly among the top ad spending firms, since the observations of high levels of overspending by Aaker and Carman (1982) and others approximately 30 years ago. Two competing predictions regarding changes in ASE over time exist. On one hand, the "overspending perspective" (inspired by Aaker and Carman's 1982 work) predicts that due to various client- and agency-side incentives and reward structures, as well as the increasingly complex media environment, overall ASE would continuously remain low over time. However, the "smart manager perspective" (broadly adapted from the organizational learning field) leads to the opposite conclusion: Overall ASE will improve over time as successful organizations and their advertising/marketing managers learn from past experience and data, thus calibrating their efforts (e.g., Dodgson 1993).

The current study tests these two competing perspectives using a nonparametric frontier approach—data envelopment analysis (DEA)—to analyze firm-level advertising spending at the aggregate level among leading U.S. marketers over the 1985 to 2012 period (Büschken 2007; Färe et al. 2004; Luo and Donthu 2001). While several studies have recently addressed the issue of the relative efficiency of advertising

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spending using DEA, the majority of prior research is characterized by analyses of one to three years' worth of annual data (e.g., Büschken 2007; Hadad, Friedman, and Israeli 2005; Luo and Donthu 2001, 2005). The DEA approach has several advantages over traditional econometric and advertising-sales response function approaches in regards to examining ASE. Applied to advertising efficiency, most econometric models essentially attempt to find an ideal spending point for each company or industry. DEA is a benchmarking methodology that examines the relative advertising efficiency among a predetermined set of advertisers (Luo and Donthu 2001). In addition, unlike the advertising response function approach, DEA allows researchers to simultaneously incorporate multiple inputs and outputs, and provides managers with realistic and actionable efficiency estimates (Büschken 2007; Charnes, Cooper, and Rhodes 1978).

BACKGROUND

Overview of Advertising Efficiency

As Danaher and Rust (1994) note, improving efficiency in advertising is essentially the same as increasing returns on investment because both are based on the ratio of inputs to outputs. Thus, early research in assessing ASE focused on ROI, the effect of advertising on sales as measured by econometric models, and advertising spending efficiency as measured by the advertising spending/sales ratio (Assmus, Farley, and Lehmann 1984). However, recently researchers have argued that competition has to be taken into account when assessing ASE as organizations do not make decisions in a vacuum (Färe et al. 2004; Lohtia, Donthu, and Yaveroglu 2007). The DEA methodology specifically incorporates competitors by measuring the performance (in this case, efficiency) of entities relative to other entities (in the current study, top 100 advertisers). Thus, in line with prior DEA-based studies, the current research operationalizes advertising efficiency as the ratio of sales to the amount spent on advertising media placement costs relative to competitors (Luo and Donthu 2005; Pergelova, Prior, and Rialp 2010).

The use of DEA to specifically analyze advertising efficiency is growing. In their seminal article using DEA to analyze adspend data for the top U.S. advertisers in 1997 and 1998, Luo and Donthu (2001) discovered that among the 63 top advertisers, 33 had low advertising efficiency (i.e., below 20%). Three years later, Färe and colleagues (2004) reported one of the few long-term investigations of ad efficiency, using U.S. media spending data from six beer companies over the 1983–1993 period. The study concludes a positive relationship between company success and advertising efficiency, although the efficiency of the overall beer brewing industry was low. Büschken (2007) reveals that among 35 brands operating in Germany's auto industry less than half (i.e., 13) use their advertising spending efficiently. More recently, Pergelova, Prior, and Rialp (2010) analyzed the impact of the Internet on adspend efficiency among 18 car dealerships operating in Spain between 2001 and 2007, concluding that consistent spending on the Internet led to increases in efficiency over the six-year period.

As noted, with two exceptions (Färe et al. 2004; Pergelova, Prior, and Rialp 2010) the majority of prior research on adspend efficiency features analyses of one to three years' worth of data (Büschken 2007; Hadad, Friedman, and Israeli 2005; Luo and Donthu 2001, 2005). Using data from one year or from a few number of years provides an incomplete understanding of how the efficiencies of large, long-surviving companies as a whole have changed over time, as the particularities of what occurs in a specific year may be nonrepresentative of efficiency across time. Indeed, because DEA estimates efficient frontiers for each single year, researchers cannot draw conclusions regarding the development of efficiency over time based on the results of previous ASE research. In the two studies that used a greater span of years, only one is based on U.S. data (Färe et al. 2004), and each focuses on a single industry (i.e., beer or car dealerships). Little is known regarding how ASE of the largest U.S. advertisers has changed since the 1980s when the work by Aaker and Carman (1982), MacNiven (1980), and Simon and Arndt (1980) brought this concern to the forefront of the industry. Certainly ad efficiency had been a concern among practitioners prior to this period, but these three pieces pushed the issue to wider prominence. The ASE of large advertisers is an important topic given that (1) adspend of the top 100 advertisers makes up approximately 49% of total national spending and (2) such entities are often used as models and bellwethers of practices due to their longevity and overall success.

Advertising Efficiency Over Time

At this point, we should note that the efficiency of a particular entity, whether at a fixed point in time or across a span of time, is driven by a very large number of interacting internal decisions and external forces. The specific effectiveness of a company's advertising efforts in impacting sales is influenced by myriad internal factors, such as the quality of messages, pursuit of a sales-oriented push strategy or an advertising-intensive pull approach, degree of focus on image maintenance versus information delivery, proper placement of messages at the vehicle level, appropriateness of target market selection, and other marketing-related actions, such as price/product changes or retail outlet expansion. The quality and impact of such considerations vary greatly from firm to firm and individual tactics may change from year to year, and thus one firm's (in)efficiency level could be the same as another's for different reasons. Furthermore, a host of factors external to the firm (and thus not capable of being directly influenced) also exists that influences sales response, including consumer confidence, the overall state of the economy, and changes in demographics

and psychographics among the populace. Analyzing the efficiency of the same group of firms at an aggregate level over a significant range of time allows broader and more generalizable conclusions that are not beholden to or limited by the particular behavior of a company, nor the extent/nature of consumer response, in a specific year.

Sales response and ad spending level/allocation do not remain exactly the same from year to year. However, the general pattern of spending is unlikely to undergo significant change over time, regardless of direction. Foundational research has demonstrated that organizational inertia is rampant, particularly among larger and older firms, such as those used in our sample of the largest U.S. advertisers (Hannan and Freeman 1984; Kelly and Amburgey 1991). As organizations get older, they likely increase in size, depth and complexity of hierarchical structure, internal politics, and bureaucracy. These lead in turn to an emphasis on predictability, formalized and more rigid roles, and control systems. Unsurprisingly, organizational behavior over time tends to become predictable and increasingly inflexible (Adams, Day, and Dougherty 1998; Hannan and Freeman 1984; Kelly and Amburgey 1991).

Given that the sample in our study is comprised of the largest U.S.-based advertisers over a 28-year period, relatively little variation over time is expected in their adspend efficiency patterns. Those that operate inefficiently are expected to do so consistently over time, while those that strive to maximize adspend efficiency are also expected to continue doing so as this kind of behavior in itself has likely become a constant and routine mode of operating for these firms. The entities in our sample will likely pursue more or less the same strategies over time, both adspend related and those that vary with adspend, and thus the strategy-variation problem is minimized. For example, whether an organization's products are in a more or less mature phase, and thus would utilize push or pull advertising strategies that likely influence ASE, this behavior would exhibit little variation over time and not be subject to systematic changes. Also, by using a relatively long time span, differences in long- versus short-term effects (i.e., differences in the stimulation of immediate sales versus the development of customer equity) would also essentially cancel out in our analysis. That larger and older entities likely will show consistent patterns of ASE over time due to organizational inertia is a conceptualization that is clearly a concern at the individual organizational level. However, it does not predict the specific direction of the efficiency (i.e. increasing or decreasing) for the group as a whole, which is the focal interest of this research. In the following section, we introduce and discuss two opposing perspectives that lead to conflicting predictions regarding the direction of overall ASE over time.

Overspending or Smart Managing?

In this section we present and discuss two competing predictions regarding general ASE over time—one based on the overspending perspective and the other on the smart manager perspective.[1] Before delving into them, however, we briefly address the issue of the impact of individual firm-level actions on ASE. Adspend efficiency is essentially comprised of two components—the input of the amount of advertising spent and the output of sales level. The amount of sales a firm sees in a given period is clearly influenced not solely by advertising but also by nonadvertising actions taken internally by the firm as well as noncontrollable external factors such consumer confidence. There have been numerous attempts to measure the impact of advertising on sales—solely, in conjunction with other marketing actions, and in comparison with external factors. Such studies have found a wide range of degrees of impact depending on the factors examined, such as industries, product types, outcome measures, levels of analysis, and many more, but the general direction of consensus is that advertising does have at least some level of impact on generating sales (see Assmus, Farley, and Lehmann 1984; Simon and Arndt 1980 for early but excellent reviews). While the output of sales is influenced by both external and internal actions, clearly decision making regarding the input of adspend level occurs within the firm. Thus, the managerial decision of how and where to spend advertising dollars is a firm-internal factor that impacts sales.

Overspending. Inspired by Aaker and Carman's (1982) work, one of the few that discusses company-level reasons for inefficiency, the overspending view predicts that overall ASE will not significantly improve over time and will in fact likely decrease due to internal organizational and external environmental factors. Initial longitudinal analyses have shown notable levels of inefficiency within the auto and beer industries in the United States and Spain (Färe et al. 2004; Pergelova, Prior, and Rialp 2010). In terms of specific media, the overspending perspective posits that given excessive spending on advertising overall, companies would particularly overspend in those media they considered as having the most beneficial impact on their sales. One reason for this pattern of general predictions is due to reward structure concerns on both the agency and client sides. Many large advertisers rely on contract ad agencies for media planning/buying recommendations. Until relatively recently, compensation has largely used a markup or commission system wherein agencies charge clients approximately 15% of all media billings (Belch and Belch 2009). Such a system encourages agency-side priorities on recommending media/vehicles based on cost, rather than efficiency or effectiveness (LaBahn 1996). Furthermore, internal prestige among account managers is often based on financial size or worth of a particular account to an agency—again, an incentive to make cost-based rather than efficiency-based spending suggestions (Aaker and Carman 1982).

On the company/client side, managers are often evaluated based on sales and market share changes. Advertising is considered an intuitive, visible, and concrete solution to declining/stagnant sales or an added driver of continuing success

when sales are increasing. At the same time, because of the difficulty and perceived cost ineffectiveness of measuring marginal returns of adspend, as well as the seemingly counterintuitive notion of reducing adspend to improve sales, client-side managers often throw more advertising at sales or share problems (Aaker and Carman 1982). Indeed, companies in a situation of having greater free cash flow have a strong tendency of overallocating money to advertising, treating it as a form of insurance against leaner times in the future when cash flow is reduced: Spend more now on advertising to minimize future negative sales and share effects when the economy and the company are faring worse (Joseph and Richardson 2002). All this is exacerbated by the increasingly complex media environment of ever-expanding vehicle and media options and a situation wherein large advertisers, such as those sampled here, commonly are served by multiple agencies operating and recommending independently of one another (Horsky 2006). Furthermore, despite such complicated environmental and situational conditions, Adams, Day, and Dougherty (1998) note that organizations often rely on routinized behaviors even when making complex decisions such as launching large-scale advertising campaigns. Thus, rather than doing what is most efficient, they will often simply do what has been done before in terms of adspend: Spend more in the face of market share/sales problems, and spend more when doing well as a form of insurance against future downturns. This constant spending as the media and competitive environments become more complex, and brands mature in age and consumer perception, results in an overall decreased level of ASE. Thus, the following is predicted:

> **H1a:** From 1985 to 2012, the overall level of advertising spending efficiency among the top 100 advertisers will decrease over time.

Smart managers. The smart manager view of ASE essentially assumes that measurement and assessment are drivers of long-term organizational survival. It draws strongly on the general organizational learning concept derived from the management and industrial psychology fields. Organizational learning assumes that successful and lasting corporate entities have attained that status due to, among other actions, constant monitoring of prior or ongoing activities, resulting in the appropriate modification of future actions (Barrie and Pace 1997; Huber 1991). As noted by Dodgson (1993) and Argyris and Schön (1978), the construct inherently revolves around improvement of efficiency within a firm being linked with success (see also Kaplan and Norton 1996). Thus, the smart manager view predicts that, while certainly not all companies or industries will do so, the overall ASE should increase over time as organizations surviving over the long term are accurately and constantly assessing adspend efficiency and making changes to spending allocations so as to utilize their dollars in the most cost-efficient manner as possible given their objectives. As a corollary, companies over time would allocate and adjust their spending allocation only to those media that are economically efficient as their products and brands mature.

While historically the 15% commission had been the predominant compensation method, advertisers are increasingly demanding accountability and ROI-based compensation systems from their agency partners. While the commission system is unlikely to entirely disappear anytime soon, the move toward compensation systems based on objective achievement, project parameters and scope, and hours worked is greatly reducing the tendency of agencies to recommend media based on cost rather than effectiveness and efficiency (LaBahn 1996; Spake et al. 1999). On the client side, the smart manager perspective assumes that employee compensation and promotion essentially is driven by company success, and thus marketing managers in organizations successful over the long term are driven to monitor adspend efficiency and modify future spending accordingly. This assumption dovetails with the fundamental tenet of free enterprise that internal competition leads to ever more effective management as only the most competent are promoted. Thus, while the media environment may be becoming more and more complex and companies are contracting with an increasing number of agencies, successful companies and their managers are able to, and must, effectively learn through measurement and maintain ASE at high levels. As each firm individually adopts this mindset and these actions (as they must to survive and thrive), collectively overall ASE increases. Thus we offer our next prediction:

> **H1b:** From 1985 to 2012, the overall level of advertising spending efficiency among the top 100 advertisers will increase over time.

METHOD

The current study develops efficient frontiers among the top U.S. advertisers, with spending in six media classes (i.e., Magazines, Newspapers, TV, Radio, Outdoor, and Internet) as input variables and U.S. sales as the output variable. By their very nature of being very large advertisers, the majority of the top advertisers from year to year represent a wide range of industries, product types, and brands. However, because the current study adopts a firm-level perspective, it is assumed that regardless of the particularities and circumstances of any one specific product type or industry, it is a key overall goal of such large advertisers to increase their ASE. First, the study identifies those advertisers operating relatively efficiently in their advertising media spending and those which are not by converting the multiple inputs (spending in the six media classes) and one output (sales in the United States) into a single efficiency score using DEA. Subsequently, the study assesses the degree to which each inefficient advertiser needs to reduce its advertising spending across six different media

classes, while maintaining the current level of output, to become efficient.

Data Envelopment Analysis. DEA is an analytical tool that has proven effective in evaluating relative efficiency (Zhu 2003). Based on economics principles, DEA is a linear programming formulation developed by management scientists and is a nonparametric approach for evaluating the relative efficiency of units within a given population. These units, referred to as decision making units (DMUs), can be any set of objects converting comparable inputs into comparable outputs (Thomas et al. 1998). As an example, the current study utilizes DEA to define a nonparametric relationship between multiple media spending inputs and outputs.

It is clear that advertisers would like to know how many outputs (in the current case, sales) they are producing for their given inputs (in this case, ad spending across the media mix); in addition, they would like to know the level of efficiency with which they are executing these actions in relation to other advertisers (Luo and Donthu 2001). However, the relative efficiency of these inputs/outputs makes the calculation of advertising efficiency more of a challenge. Because each DMU's efficiency is estimated relative to other units in the sample (Thomas et al. 1998), the term *relative efficiency* is utilized. Advertisers are efficient if no other advertiser, or linear combination of advertisers, expends less of every input (given outputs) and equals or exceeds the quantity of their output (given inputs) (Farrell 1957). In contrast to ordinary econometric analyses, DEA does not assume functional form connecting the inputs and outputs. Consequently, DEA calculates each advertiser's efficiency relative to that of all other advertisers, with the single limitation that all advertisers lie on or below an "efficient frontier" (Luo and Donthu 2001).

The DEA method creates an efficient frontier by incorporating multiple inputs and multiple outputs and computing a DMU's efficiency by ascertaining the minimum possible inputs needed to capture a set of outputs (input orientation) or by calculating the maximum possible outputs that a given set of inputs generates (output orientation) (Parsons 1992). In the instance of measuring ASE, an input orientation model focuses on maximal movement toward the efficient frontier through proportional reduction of inputs such as media spending, whereas an output-oriented model focuses on maximal movement via proportional augmentation of outputs such as sales (Charnes et al. 1994). DEA then sets an efficiency score of one for efficient advertisers, while the inefficient advertisers' efficiency scores are less than one but greater than zero (Zhu 2003).

Here we note that if the relative importance advertising plays in the strategies of the organizations in our sample varies significantly, there will likely be a different optimal frontier than the one we used, thus making the analysis invalid. Our study and method assume constancy/stability in the importance of advertising to the organizations in the sample. While the importance of advertising to any one particular advertiser will certainly vary to some degree over the 28-year period, we feel the assumption of general constancy in the importance of advertising to the sample as a whole is valid. Given the nature of these entities as generally very large, large-spending, and long-surviving organizations in the United States, the vast majority operate in multiple product categories, markets, price points, and so on (e.g., Procter & Gamble). Even those that may operate in only one main category (e.g., General Motors) most likely are managing brands, subbrands, and lines at myriad levels, in multiple markets, and pursuing an extensive variety of target consumers. These organizations are constantly releasing and supporting new products, brands, extensions, and versions. Thus, while the importance of advertising to a specific product likely changes over time depending on its life cycle, due to the constant addition of new (versions of) product/brands that is a common characteristic of such large companies the importance of advertising to the organizations in general is likely to stay constant overall.

Analysis Technique

Input-oriented model. This study utilizes an input-oriented model (Charnes, Cooper, and Rhodes 1978). As Donthu, Hershberger, and Osmonbekov (2005) pointed out, there is no reason to believe that either the inputs or outputs should be more heavily weighted in a DEA analysis. When measuring ASE, some studies (e.g., Luo and Donthu 2001; Büschken 2007) have used an input-oriented model, because advertising managers can be presupposed to have more direct control over the inputs (i.e., how much they spend on advertising) than over the output (in this case, company sales); others (Pergelova, Prior, and Rialp 2010) have employed an output-oriented model, as advertising budgets can be preliminarily decided and the objective can be the maximization of output with the available budget.

Variable return to scale (VRS). Variable return to scale (VRS) is utilized in the current model. It is possible to specify DEA under different assumptions regarding returns to scale. To figure efficiency scores by employing DEA, two different assumptions are possible: constant return to scale (CRS) and VRS. The CRS assumption prevails when changing all inputs by one proportion alters the outputs by the same proportion. In the instance of CRS, it is assumed that every firm operates at optimal scale. If, however, the CRS assumption is not satisfied, or if changing all inputs by some proportion alters the output by less or more than that proportion (Cooper, Seiford, and Tone 2006), then the VRS assumption is activated. Indeed, firms frequently do not operate at optimal scale. For that reason, DEA can be specified with VRS, meaning that input increases result in disproportional output increases.

Accordingly, in our study, efficiency values are calculated assuming input orientation and VRS, using advertising spending in the six media categories (i.e., TV, radio, Internet, magazines, newspapers, and outdoor) as the inputs and sales as the

output variable. The model is specified in the following equation:

$$Min\,\theta - \varepsilon\left(\sum_{i=1}^{I} s_i^- + \sum_{r=1}^{R} s_r^+\right)$$

$$\sum_{j=1}^{J} \lambda_j x_{ij} + s_i^- = \theta_o x_{i0}, \sum_{j=1}^{J} \lambda_j y_{rj} - s_r^+ = y_{r0}$$

$$\lambda_j \geq 0, \sum_{j=1}^{J} \lambda_j = 1$$

where x_{ij} = advertising spending in the i media categories (i.e., TV, radio, Internet, magazine, newspaper, and outdoor) $i = 1, \ldots I$, I = total number of inputs; y_{rj} = sales, $r = 1, \ldots R$, R = total number of outputs; $j = 1, \ldots J$, J = total number of DMUs; θ_0 = the efficiency score of a focal DMU; λ_j = the weight value assigned to the jth reference, s_i^- and s_r^+ represent input and output slacks, ε is non-Archimedean, permitting minimization over θ.

A detailed illustration of how this DEA model has been derived is presented in the Appendix.

Solving this DEA model results in optimal solutions of θ^* and λ^*. Otherwise stated, the oth advertisers' inputs are minimized through θ^*, as much as the constraints will allow proportion (Cooper, Seiford, and Tone 2006). If the efficiency score θ^*equals 1, the current input levels are optimally efficient, signifying that the DMUs are on the efficient frontier. If the efficiency score $\theta^*$is less than 1, the current input levels are inefficient, which signifies that the DMUs are in the area dominated by the efficient curve. Such an inefficient DMU (i.e., an inefficient advertiser) should reduce the current inputs to the level of its reference sets, represented by λ^*. Slacks (i.e., s^+ and s^-) exist solely for the leftover proportions of inefficiencies. After proportional reductions in inputs or outputs, if a DMU cannot reach the efficiency frontier line, slacks are needed to push the DMU to the efficiency frontier line. Input slacks indicate immediate efficiency gains by reducing advertising media expenditure (Cooper, Seiford, and Tone 2006).

Study Variables and Data

To determine DEA efficiency scores, six inputs (magazines, newspapers, TV, radio, outdoor, and Internet) and one output (total sales) were used. *Advertising Age*'s annual "100 Leading National Advertisers" issue provided the data on both advertising spending in different media and total sales. *Advertising Age* reports a company's advertising media spending in dollar amounts, as calculated by the TNS tracking company, in six specific media classes.

The amount of magazine spending is an aggregation of company spending in national magazines, Sunday magazines, local magazines, and business-to-business (B2B) magazines. Newspaper spending includes combined data based on adspend in local papers, national papers, and Spanish-language newspapers. TV spending is the summation of network TV, cable networks, spot TV, syndicated TV, and Spanish-language TV networks. Radio spending is the aggregated amount spent in local radio, national spot radio, and network radio. Data on Internet spending starts being reported in 1997 and includes estimates based on more than 2,500 sites each year (excluding paid search and broadband video ads). The descriptive statistics for these six inputs and one output are shown in Tables 1 and 2.

RESULTS

The current study uses DEA Excel Solver LV V3 (Cooper, Seiford, and Tone 2006) for data analysis. Table 1 presents the distribution of the variables used to measure media spending efficiency for the period 1985–2012, with the aim of understanding year-specific output and inputs of the top advertisers. Although *Advertising Age* reports data on the top 100 advertisers, Table 1 shows that the total number of advertisers reported varies each year because not all advertisers provide sales data in a given year. The total average output fluctuated but increased overall from 1985 to 2012. For inputs, media expenditures in general rose each year with some fluctuations from 1985 to 2012 as the average total output increased. When applying DEA, inputs and outputs should be positively correlated to allow for the influence of inputs on outputs (Luo and Donthu 2001). Table 2 reports all positive correlation coefficients between inputs and output, making these six types of media spending—magazines, newspapers, TV, radio, outdoor, and Internet—eligible for DEA analysis.

Three media spending items are noteworthy: TV, newspapers, and Internet. Constituting the largest portion of total average media spending in 1985 at 70%, TV spending declined to 65% by 2012. The share of newspapers fluctuates over time but overall is rather stable, accounting for 6% of total media spending in 1985 and 6% in 2012. The Internet showed the greatest increase, accounting for 0.4% of total media spending in 1997 but growing to 8% by 2012, a mere 16 years, after which it accounts for a larger share of total media spending than both radio and outdoor.

Meanwhile, in general, the share of magazines is stable over time, accounting for 17% of total media spending in 1985 and 16% in 2012. The share of radio fluctuates over time but overall is rather stable, accounting for 4% of total media spending in 1985 and 4% in 2012. The share of outdoor media spending is also stable but overall decreased over time, accounting for 2.3% in 1985 and 1.9% in 2012.

In summary, the advertising industry saw a big increase in the proportion of total average media spending in the Internet,

TABLE 1
Descriptive Statistics of Advertising Media Spending and Sales

Year	*N*	Magazines	Newspapers	TV	Radio	Outdoor	Internet	Sales
1985	61	27.62	10.60	114.31	7.06	3.74	—	7,981.31
1986	53	27.93	9.93	108.56	8.55	4.00	—	7,981.31
1987	52	28.93	10.65	124.34	17.20	3.61	—	8,983.96
1988	68	28.60	20.45	131.27	10.74	2.39	—	15,847.37
1989	48	42.78	11.87	164.11	12.16	3.33	—	12,057.54
1990	52	37.39	8.90	181.40	66.16	3.77	—	10,386.74
1991	55	41.56	5.61	167.67	6.56	3.79	—	11,099.22
1992	50	45.16	13.06	171.89	7.18	2.86	—	12,636.35
1993	59	46.38	15.22	182.99	6.68	2.44	—	12,664.20
1994	60	52.38	17.25	207.37	6.59	3.30	—	17,919.70
1995	95	49.65	33.59	190.16	8.22	3.63	—	15,606.41
1996	74	49.33	32.95	196.63	9.33	3.59	—	14,827.98
1997	91	57.92	43.43	220.54	9.72	3.56	1.27	16,257.46
1998	94	62.80	47.91	236.94	9.68	4.86	1.65	12,382.76
1999	94	73.99	62.21	257.11	9.71	4.84	3.71	19,939.04
2000	82	75.99	68.29	296.15	21.10	5.40	3.66	21,588.31
2001	93	75.30	66.28	274.70	11.48	6.14	5.75	22,563.35
2002	90	79.92	68.59	293.40	14.04	5.95	14.04	23,858.00
2003	94	93.78	78.74	322.55	16.60	6.47	12.14	22,805.28
2004	91	103.06	86.86	361.37	15.69	8.52	23.63	24,453.81
2005	93	110.87	89.49	356.02	34.81	9.89	27.84	26,356.76
2006	95	105.76	79.83	352.81	34.81	10.37	33.70	27,416.64
2007	91	109.41	74.85	352.34	32.58	10.89	42.49	28,429.23
2008	68	98.44	58.96	339.51	25.72	9.37	29.68	25,783.72
2009	69	97.69	52.91	321.74	20.19	7.66	37.92	26,172.78
2010	54	113.75	45.62	363.64	20.12	9.31	38.40	27,306.39
2011	64	91.64	35.67	345.30	19.44	10.03	42.62	26,133.67
2012	61	85.07	34.29	357.27	22.06	10.44	44.62	28,729.57
Mean		68.33	42.29	249.72	17.29	5.86	22.47	22,843.10
SD		28.90	27.34	87.84	12.81	2.86	16.42	20,944.35

Note. All entries are in millions of dollars.

while having almost no change in the proportion of total average media spending for newspapers, magazines, and radio, and decreases in TV and outdoor.

Hypotheses 1a and 1b: Overspending or Smart Managing?

Hypotheses 1a and 1b focus on the broad pattern of changes in advertising efficiency during the years 1985–2012 among the top U.S. advertisers. Table 3 presents the numbers of efficient and inefficient advertisers obtained for each of the 28 years. Overall, 39% of the top advertisers in this study are classified as efficient and the rest as inefficient, meaning that 61% of the top advertisers could further reduce adspending while producing the same amount of sales. Based on the DEA, 28% of the top advertisers demonstrated low advertising efficiency (below 20%), indicating a lot of waste in advertising from 1985 to 2012. Table 3 shows that, while the proportion of inefficient firms fluctuated year to year, the proportion of inefficient firms overall increased from 1985 (52.46%) to 2012 (75.41%). In line with Table 3, Table 4 shows that the efficiency score also decreased over time from 0.77 in 1985 to 0.52 in 2012 with a few fluctuations. Thus our results support hypothesis 1a (the overspending perspective) in that, overall, the level of efficiency has declined since 1985.

Figure 1 shows that the mean efficiency score of all leading advertisers for the 28 years was 0.66, which means that advertisers needed to produce sales using approximately 34% fewer inputs than they did over the 28 years to become efficient.

A 32% decrease in average efficiency scores occurred in 2012 relative to 1992 and overall an 25% decrease in 2012 relative to 1985. Comparing the difference in the number of inefficient advertisers during the Internet period (1997–2012)

TABLE 2
Correlation Matrix of Advertising Media Spending and Sales

Media	Magazines	Newspapers	TV	Radio	Outdoor	Internet	Sales
Magazines	1.00	.19**	.08*	.16**	.32**	.30**	.10**
Newspapers	.19**	1.00	.18**	.38**	.31**	.35**	.06*
TV	.08*	.18**	1.00	.08*	.08*	.06*	.15**
Radio	.16**	.38**	.08*	1.00	.37**	.32**	.15**
Outdoor	.32**	.31**	.06*	.37**	1.00	.33**	.06*
Internet	.30**	.35**	.06*	.32**	.33**	1.00	.06*
Sales	.10**	.06*	.15**	.06*	.06*	.06*	1.00

*$p < .01$; **$p < .05$.

versus non-Internet (1985–1996), the average percentage of inefficient advertisers during the Internet period was 73.5% versus 60.8% when Internet spending was not reported. In short, the findings reveal deterioration in efficient media spending over the 28-year time span.

Additional Analysis of Spending Inefficiency

To shed greater light on the inefficiencies of advertising spending in each medium (slack), we conducted additional analyses. Slack is derived using an input-based approach (Cooper, Seiford, and Zhou 2000). DEA identifies excess input for each input and each advertiser. Table 4 reports the mean slacks per input and year. The slack entries are positive, indicating that advertisers' spending in various media is in excess compared to efficient advertisers. The slack analysis also suggests that much of the advertising spending across all six media classes could have been reduced while maintaining the same sales levels for the past 28 years. Outdoor has the lowest overall slack and TV has the highest overall slack across 1985–2012. In fact, the inefficient advertisers among the top 100 have to cut $4.75 million per year in magazines, $4.73 million per year in newspapers, $14.44 million per year in TV, $1.59 million per year in radio, and $1.04 million per year in outdoor while obtaining the same sales to be considered efficient during the period 1985–2012. Interestingly, the total amount of slack for Internet spending is greater than that of outdoor despite its relatively short period of existence and use. The efficient advertisers among the top 100 have to cut $2 million per year during the period 1997–2012.

The average amount of slacks in TV during the years 1985–2012 is the largest and magazines provide the second largest, followed by newspapers. Figure 2 illustrates the fluctuations of slacks for each of the six media breakdowns from 1985 through 2012. It clearly shows that the slack amount for TV has been greater than for other media during most of the years examined. Figure 2 also shows that, during the recent 2002–2012 period, TV, magazines, and newspapers have contributed most to the overall slack amount.

DISCUSSION, LIMITATIONS, AND FUTURE DIRECTIONS

One of the main goals of the current study is to assess whether top U.S. advertisers are becoming more or less efficient over time. The overspending perspective predicts that, due to various internal and external structural conditions and incentives, the majority of companies will not only continue to be inefficient but will become more inefficient when it comes to ad spending. The contrasting smart manager hypothesis drawn from the organizational learning literature predicts the opposite: large, long-surviving entities learn from prior experiences and mistakes, and are constantly improving efficiency to stay in business and increase revenues, thus advertising efficiency should improve over time.

Our results show a clear overall increase in inefficiency among the top 100 U.S. advertisers between 1985 and 2012, thus providing support for the overspending hypothesis. Indeed, Table 3 shows that during the mid-1980s slightly more than 50% of top advertisers were inefficient in their adspend, and this percentage increased to approximately 69% of firms in the latter half of the 2000s. Furthermore, the sample is overspending by an average of 34%. While efficiencies in other areas of organizational operations may be improving, the data show that as a whole the largest advertisers in the United States are not improving in their adspend efficiency. While direct comparison of our results to prior studies, such as those of Luo and Donthu (2001, 2005) and Büschken (2007), is challenging given the different media types, industries, countries, and range of years analyzed, the current study's results are generally in line with prior DEA-based analyses of ASE in that the large majority of advertisers are using their ad dollars inefficiently.

On the surface, adspend inefficiency becoming worse over time is rather surprising and counterintuitive. The advertisers analyzed in the current work are highly experienced organizations with regards to marketing practice, have significant marketing budgets, and have survived in the highly competitive U.S. marketplace for a long time. Indeed, the core finding—

TABLE 3
Comparative Efficiency Results by Year (Derived from VRS Input Model)

		Efficient		Inefficient	
Year	*N*	*N*	%	*N*	%
1985	61	29	47.54	32	52.46
1986	53	26	49.06	27	50.94
1987	52	22	42.31	30	57.59
1988	68	30	44.12	38	55.88
1989	48	23	47.92	25	52.08
1990	52	27	51.92	25	48.08
1991	55	27	49.09	28	50.91
1992	50	32	64.00	18	36.00
1993	59	33	55.93	26	44.07
1994	60	23	38.33	37	61.67
1995	95	33	34.74	62	65.26
1996	74	28	37.84	46	62.16
1997	91	34	37.36	57	62.64
1998	94	32	34.04	62	65.96
1999	94	35	37.23	59	62.77
2000	82	22	26.83	60	73.17
2001	93	30	32.26	63	67.74
2002	90	31	34.44	59	65.56
2003	94	30	31.91	64	68.09
2004	91	37	40.66	54	59.34
2005	93	31	33.33	62	66.67
2006	95	35	36.84	60	63.16
2007	91	32	35.16	59	64.84
2008	68	20	29.41	48	70.59
2009	69	20	29.00	49	71.00
2010	54	15	27.78	39	72.22
2011	64	16	25.00	48	75.00
2012	61	15	24.59	46	75.41
Total	2,051				
Average			39%		61%

that extensive individual practice and repetition of tasks results in increased task competence over time (Ericsson, Krampe, and Tesch-Römer 1993)—has general support at the organizational level as exemplified by the learning curve: As organizations gain experience over time, their capacities to adapt and learn increase, and in turn better performance results (Dutton, Thomas, and Butler 1984; Levitt and March 1988); thus the expectation that our sample of large consumer-facing advertisers would demonstrate wise and highly efficient use of their dollars when advertising. However, our results indicate that, at least in terms of advertising spending, this learning curve is more of an ideal than a norm. In the early stages of their existence, organizations may learn and adapt, but as they succeed and endure over time they formalize internal relationships and establish routinized patterns of operation—in other words, structural stability and inertia tends to increase as firms endure. However, the increasing stability comes with a price: an increasing resistance to change and a decreased ability to continuously and nimbly adapt to changing circumstances (Gresov, Haveman, and Oliva 1993; Hannan and Freeman 1984). Large and enduring organizations may truly be victims of their own success with regard to efficiency. We recommend that future studies compare adspend efficiencies between large and small advertisers. Smaller and newer entities likely have more limited advertising budgets than their larger counterparts and may be more concerned with achieving the highest ROI from their media spending because inefficiencies impact them more strongly, potentially harming their chances of survival at all. Such entities are also likely to have fewer hierarchical structures that facilitate more flexible and faster decision-making capabilities. Thus, comparing both small and large organizations' ASEs would expand our knowledge by indicating whether the inefficiencies found in the current study are driven by the significant size and endurability of the sample. If results show that even smaller/newer organizations exhibit similar levels of adspend inefficiency, it would indicate something about the particular nature of advertising spending is driving the inefficiency.

The current research findings are also surprising given ongoing changes in agency compensation. In the past, clients compensated advertising agencies through a commission system based on media billings. Such a system encourages the recommendation of amounts and types of media spending that yield the most return to agencies, rather than spending that yields the most efficient and effective sales results. However, agency compensation is rapidly evolving, in large part due to client demand, into return-on-results systems that should in theory minimize/reduce such agency proclivities (Zhao 2005). Despite this change in compensation methods, results from the current research show little change in enhancing efficiencies, at least among the largest advertisers. This indicates that the main sources of ASE are not from outside contractors such as agencies but originate internally within client firms.

While there is a growing literature investigating marketing communication spending efficiency, and many such studies attempt to pinpoint the specific source(s) of inefficiency (e.g., spending in outdoor or certain geographic areas), virtually all work in this area, including ours, adopts a very high level view that looks solely at inputs and outputs. No studies in this area have specifically examined the causes or antecedents of ASE. This is particularly important when considering efficiency over the long term; one or two years of inefficiency may simply be chance or an aberration, but decades of it is a clear pattern of occurrence. Fundamentally, this is an issue of organizational learning that involves the human component: While organizations may exhibit certain levels of inefficiency, it is the people in those organizations that make the decisions and take the actions that lead to those results.

TABLE 4
Average Slacks per Year and Media (Derived from VRS Input Model)

Year	*N*	Efficiency	Magazines	Newspapers	TV	Radio	Outdoor	Internet
1985	32	.77	.72	.69	5.96	1.03	.51	—
1986	27	.71	.86	.46	1.26	.25	.38	—
1987	30	.71	1.49	.36	10.14	2.29	.42	—
1988	38	.68	.22	.02	2.63	.66	.08	—
1989	25	.74	.42	.09	10.32	1.31	.47	—
1990	25	.81	3.60	.36	20.85	2.09	1.04	—
1991	28	.76	8.32	.24	38.88	1.08	1.37	—
1992	18	.84	1.35	1.74	4.15	.45	.19	—
1993	26	.79	3.50	.47	17.63	.46	.89	—
1994	37	.65	1.34	1.93	7.55	.97	.34	—
1995	62	.68	2.29	4.65	21.07	2.05	.69	—
1996	46	.68	2.78	2.25	3.18	1.72	.26	—
1997	66	.63	4.40	3.80	11.39	1.28	1.05	.35
1998	62	.67	3.45	3.64	7.20	1.49	.82	.30
1999	59	.65	5.22	2.10	13.61	1.51	.67	.96
2000	60	.60	5.67	4.19	5.28	4.08	1.02	.95
2001	63	.61	6.65	1.89	13.00	1.19	1.36	.80
2002	59	.62	8.76	11.14	8.30	1.04	1.25	2.46
2003	64	.61	7.59	9.60	3.93	1.74	1.37	2.30
2004	54	.67	8.70	13.06	17.55	.27	1.74	4.33
2005	62	.63	8.05	13.30	17.69	.42	1.62	1.95
2006	60	.64	8.83	12.81	15.44	1.35	1.48	1.47
2007	59	.66	4.16	8.02	24.49	2.29	1.28	5.39
2008	68	.60	7.50	7.09	24.78	3.25	1.37	1.03
2009	69	.56	7.21	8.37	21.71	2.96	1.47	2.25
2010	54	.55	6.71	6.14	41.55	2.65	1.71	3.18
2011	64	.52	8.74	7.26	16.29	1.80	1.83	3.59
2012	61	.52	4.60	6.73	18.36	2.96	2.41	2.26
Total	2,051		133.21	132.40	404.19	44.64	29.09	29.98
Average		.66	4.75	4.73	14.44	1.59	1.04	2.00

Note. Internet spending was not reported by *Advertising Age* prior to 1997. All entries are in millions of dollars. Total number of advertisers indicates the number of inefficient advertisers which have slacks on media spending; correlations of efficiency scores between CRS and VRS = .88.

To expand the scope of ASE knowledge, we recommend that future research in the area not only take a DEA input-output approach but also supplement these data with assessments of drivers of organizational learning within the sampled organizations. Core drivers include an organization's climate for learning (i.e., the extent to which it supports and encourages employee learning), quality and quantity of information dissemination processes within the firm, and the level of individual knowledge and extent of individual learning effort exhibited by employees (Bell, Mengüç and Widing 2010; Fiol 1994; Huber 1991). Such investigations into organizational learning typically utilize surveys of managers and other employees within the firm. This would very likely pragmatically necessitate a very limited range of years by which to analyze adspend efficiency using DEA, but this would be offset by the valuable survey data demonstrating the specific internal sources and causes of advertising inefficiency.

The role of advertising agencies in this process should likewise not be ignored. Ultimately, firms clearly have the final say over how, where, and when their advertising budgets are spent. However, a key advisor and influence over such decisions and actions are said agencies. To our knowledge, no studies have yet investigated the operating and marketing efficiency of ad agencies themselves. Such information would be meaningful; after all, agencies are revenue-generating entities as well. If they do not themselves operate very efficiently it is unlikely they will factor such concerns when giving advice and suggestions to their

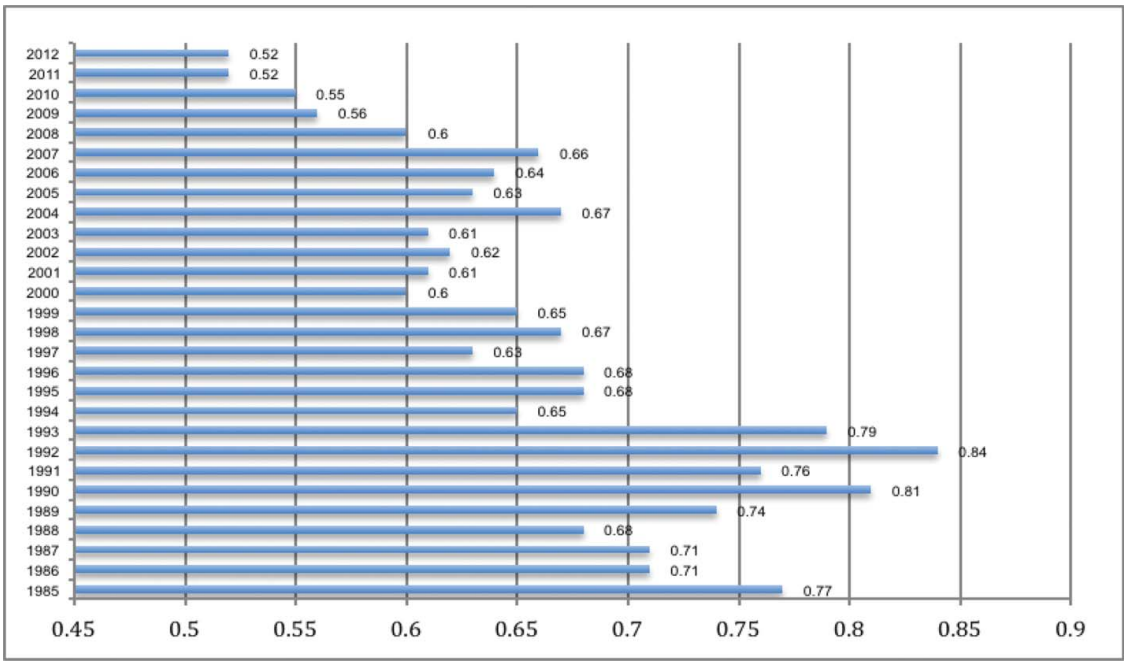

FIG. 1. Year-specific mean efficiency scores of top advertisers.

clients. This is likely not out of some cavalier disregard for the issue but simply that agencies may not really be aware of their own efficiencies, or lack thereof, and thus it may not be a consideration in their client dealings.

The competing smart manager hypothesis is drawn from the organizational learning literature. And though our results do not find support for the prediction that overall ASE should improve over time, we hesitate to infer that there is a lack of learning occurring at all, nor do we wish to give the impression that all the firms in our sample are overspending. In fact, Tables 3 and 4 indicate that from 1995 to 2007, notwithstanding a few sharp fluctuations, the level of inefficiency was

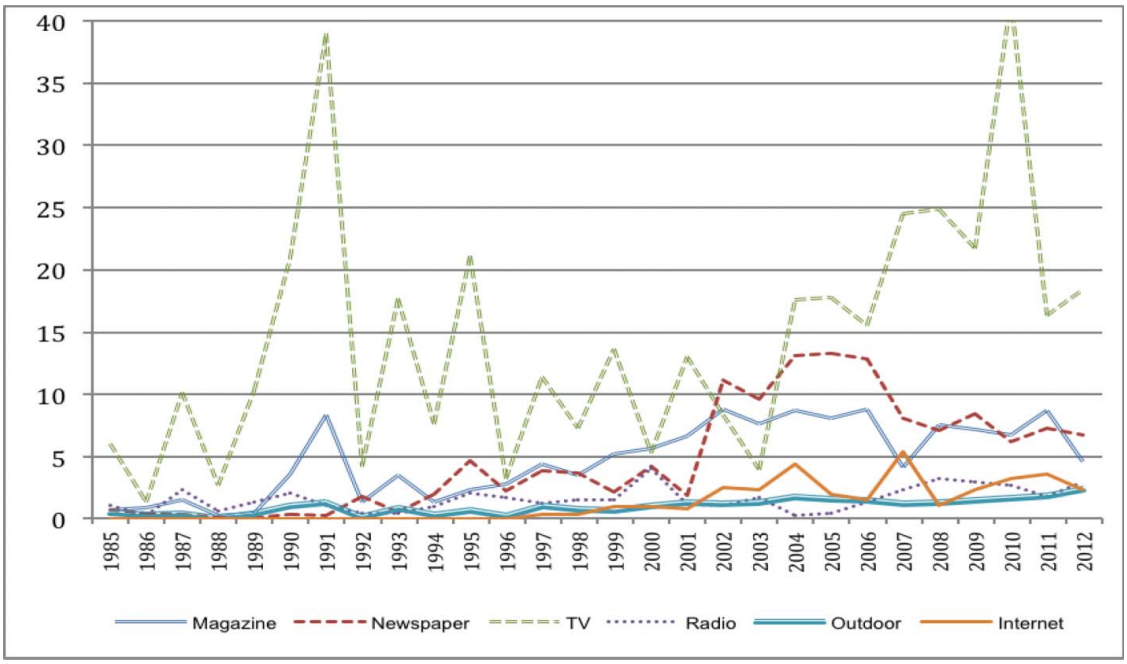

FIG. 2. Average slacks per media class and year.

rather steady in terms of both the number of inefficient firms and average efficiency. Given that during this period the media and competitive environments increased in complexity, the relatively constant rate of inefficiency would seem to indicate some corporate-level learning occurring as these large, long-surviving firms adjust to survive. However, it is also clear that the more recent 2008–2012 period saw a distinct increase in inefficiency; indeed, it is at its highest level across the 28-year period of our study. Thus, this hold in the inefficiency rate from 1995 to 2007 does not mitigate the conclusion that, overall, from 1985–2012 as a group, the largest U.S. advertisers have experienced an increase in inefficiency. While organizational learning is very likely going on at individual organizations it cannot be escaped that approximately 67% of the biggest advertisers over this period are inefficient in their ASE.

As noted above, learning and improvement are almost certainly going on in individual entities given that many of the top advertisers survived over the 28-year period and the inefficiency rate held steady over 1995 to 2007, there has also been a concomitant and constant increase in the complexity of the media environment. Every year more and different media/vehicle options appear, particularly since the Internet began flourishing as a marketing communications tool. Indeed, one of the reasons for the exponential growth in Internet advertising spending from 1997 to 2012 is the ability for advertisers to more easily and efficiently track consumer actions in comparison with other media types. However, Tables 3 and 4 indicate that the Internet's advent as an advertising medium during this period had not had any overall impact up to 2012. Indeed, during the 2008–2012 period, when the Internet truly became a core advertising medium, the level of inefficiency has risen to its highest levels across our 28-year time span.

This finding contrasts with Pergelova, Prior, and Rialp's (2010) study, which found interactive media making a contribution toward increased efficiency from 2001 to 2007. The reason for the discrepancy in results of the two studies may be that Pergelova and colleagues (2010) examined ASE among a smaller sample of advertisers (18) within one industry (car dealers) in a different country (Spain). Thus, it may be that car dealers in Spain (a smaller market than the United States) have been able to more efficiently utilize the Internet in their media spending than the largest advertisers in the United States, but each operates in very different environments.

One reason for our results may be that, partly due to the size of the U.S. market and the sheer number of potential consumers, the Internet has been characterized by constantly changing and emerging ad forms/options/pricing models. Coupled with the reverse problem of other media—rather than too few or ineffective ways to measure audience response—the Internet has too many ways with no industry consensus as to best practices in measurement. As of 2012 the medium had not impacted the ability of marketers to advertise more efficiently. We speculate that this may be due to advertisers still being in a phase of experimenting with the burgeoning forms of interactive media and thus slowly developing a better understanding of it (i.e., managing smarter when it comes to Internet utilization). One clear implication of our findings is that the medium does not provide an automatic benefit to efficiency, despite its other numerous advantages, compared to other media. Much like the literature demonstrating that simply having or implementing large-scale CRM technologies does not automatically result in successful/improved customer retention, despite the Internet's lower overall cost, greater audience tracking capabilities, and generally hyped trade media coverage, online spending must be carefully tracked and managed for gains in efficiency coupled with clear objectives in relation to said efficiency levels (Foss, Stone, and Ekinci 2008; Payne and Frow 2006).

We suggest that, despite the Internet as of 2012 not seeming to impact ASE, organizations continue to refine their efforts in the medium; indeed, they must, given that it is such a significant part of many consumers' lives. Certainly the Internet has great potential for efficiency enhancement due to its tracking capabilities, relatively low overall cost, and flexibility of ad placement (for an excellent overview, see Pergelova, Prior, and Rialp 2010). As the newest media form, it is not surprising that there is still wide variation in its effective utilization, but its potential currently outweighs any limits to efficiency contribution.

In addition, future research can use more detailed breakdowns of media advertising spending (e.g., network TV versus spot TV) to give more depth to the analysis. In particular, as a result of the constantly increasing types and models of Internet advertising options, we strongly recommend that future studies incorporating this medium utilize more detailed breakdowns of spending in this medium so its full impact may be better assessed. For example, our source of data did not include paid search when reporting Internet advertising spending amounts, yet this type of Internet advertising grew to account for around 48% of interactive advertising revenues in the United States in 2012, up from 46% in 2011 (Interactive Advertising Bureau, 2012). In light of ever-changing and an increasing number of interactive media options for advertising that have appeared since 2012, future ASE research must incorporate more comprehensive Internet breakdowns.

Second, in line with most prior DEA-based investigations of adspend efficiency, our study operationalized advertising efficiency as the ratio of media spending level to sales in the same year. However, such an approach does not specifically account for carryover effects of advertising. Such effects have been found to last from only a few months to five years, with consensus evolving that carryover cannot be simply stated as being of a specific duration in general but is highly influenced by product category, media used, age of the product/market, and ad creative cues (e.g., Sethuraman and Tellis 1991; Tellis and Weiss 1995). Given that our sample comprised a large number of very diverse types of organizations operating in

multiple product categories and over a significant duration, there is great difficulty in estimating elasticity of the effects of advertising across such wide-ranging types of entities. Thus, we adopted the common practice of defining advertising efficiency as the ratio of media spending level to sales in the same year. Given that our analysis is at a broad, macro level, the specific carryover durations or effects experienced by a particular organization do not hamper our overall ability to analyze general patterns of efficiency changes over the time frame. However, to more comprehensively evaluate advertising efficiency, future efforts need to better and more specifically incorporate lagged carryover effects into their models and analyses.

Another potential critique of our approach of conducting DEA-based advertising efficiency analysis solely using media spending inputs and sales outputs is that it does not provide a means of understanding why spending and sales are (in)efficient and implies that advertising is the sole or main influencer of sales. Certainly it is not simply the inefficient allocation of dollars to media that is impacting sales. Myriad internal factors, such as ad content, target selection, product positioning strategy, the internal decision making of firm managers explored earlier in our discussion, as well as external factors such as economic conditions, are combining to limit sales impact. However, given that consumer-facing organizations in the end have as their overall ideal objective the increase of sales of their products, the allocation of dollars to media is a fundamental advertising decision bearing the underlying assumption that such actions have an impact on said sales, whether directly or indirectly. Thus, our choice to use media spending as inputs.

As our goal in the current research was to investigate the general pattern of adspend (in)efficiency over time, we selected the top U.S. advertisers in terms of ad dollars spent in each year as our sample, with our data originating from *Advertising Age*'s annual report. These companies are for the most part very large entities comprising a very diverse range of brands, target audiences, price points, department structures, and agencies used. Coupled with the extensive 28-year time frame, we could not comprehensively incorporate additional general marketing- and organizational-level variables to empirically assess potential causes of the observed patterns of (in)efficiency over time. We strongly recommend future studies of adspend efficiency begin to focus on such specific causes/variables of (in)efficiency. Such studies could utilize shorter time spans and restrict themselves to one or two types of entities in specific industries or product categories (e.g., publicly traded consumer packaged goods companies over a 10-year span), thus increasing the feasibility of incorporating explanatory variables beyond the media spending and sales amounts used in our work. One of the few studies that takes an expanded approach to this issue reveals that in the German car market ASE increases as size of an organization's product portfolio expands and inefficiency increases as brand preference declines (Büschken 2007). Furthermore, the impact of advertising inefficiency needs greater attention, as it may not be limited to sales effects. A recent study tracking 56 large organizations' advertising from 2004 to 2007 revealed that, while more than 50 percent were inefficient in their spending in any given year, the efficient firms showed outsized positive stock returns compared to their inefficient counterparts (Raithel et al. 2011).

In summary, our results show a clear general pattern of increasingly inefficient adspending among the largest advertisers in the United States; overspending by an average of 34%; and that, up to 2012, the Internet had not had any impact overall on efficiency. This despite the increasing demands for demonstrating ROI for marketing actions and an online environment featuring a voluminous amount of relatively easily collectable data on consumer actions and perceptions. Advertising managers and agency practitioners should take heed of these results, as they signal an ongoing concern in the way marketing communications processes are conducted. As our results and discussion indicate, there exists great room and multiple fruitful future directions for researchers to shed much further light on the causes, outcomes, and nature of advertising inefficiency.

NOTE

1. We thank an anonymous reviewer for guidance and suggestions regarding the concepts of the overspending perspective and the smart manager perspective.

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APPENDIX

Model Specification

Suppose there are *J* DMUs (Decision Making Units—in the current study, top advertisers), and that there are *I* inputs and *R* outputs for the DMU being considered.

Let the *j*-th DMU produce outputs y_{rj} using x_{ij} inputs. The ratio of weighted outputs to weighted inputs for the DMU being considered are maximized, subject to the assumption that the similar ratios for all DMUs be less than or equal to 1. Accordingly, a model for computing the efficiency of *j*-th DMU is given here:

$$Max \frac{\sum_{r=1}^{R} v_{rj} y_{rj}}{\sum_{i=1}^{I} u_{ij} x_{ij}} \qquad \text{Model (A)}$$

Subject to, $v_{rj}, u_{ij} \geq 0$: the weights to be ascertained by the above mathematical program.

where the subscript *i* stands for inputs ($I = 1, 2 \ldots I$), *r* stands for outputs ($r = 1, 2, \ldots R$) and *j* stands for the DMUs (DMU = $1, 2, \ldots J$). The subscript *j* denotes the DMU being considered.

Because of the fractional objective function of the above program, it is difficult to solve. Consequently, the denominator of the ratio should be unified (i.e., one); then the objective function becomes linear, and a linear programming problem can be obtained below:

$$Max \sum_{r=1}^{R} v_{rj} y_{rj} \qquad \text{Model (B)}$$

$$\text{Subject to,} \sum_{i=1}^{I} u_{ij} x_{ij} = 1, \sum_{r=1}^{R} v_{rj} y_{rj} - \sum_{i=1}^{I} u_{ij} x_{ij} \leq 0.$$

A full DEA model involves the solution of *J* such programs, each for a base DMU, yielding *J* different set of v_{rj} and u_{ij}weights. In every program, the ratio to be maximized is changed, while the constraints are the same. Using the duality in linear model, an equivalent envelopment form of Model (B) can be obtained. The envelopment form entails fewer constraints than the multiplier form; consequently, the computation of the efficiency score is usually executed with the dual of Model (B). The dual, rating *j*-th DUM, is given as follows:

$$Min\theta - \varepsilon \left(\sum_{i=1}^{I} S_i^- + \sum_{r=1}^{R} S_r^+ \right) \qquad \text{Model (C)}$$

$$\sum_{j=1}^{J} \lambda_j x_{ij} + s_i^- = \theta_j x_{ij}, i = 1, \ldots I$$

$$\sum_{j=1}^{J} \lambda_j y_{rj} - s_r^+ = y_{rj}, r = 1 \ldots R$$

$$\sum_{j=1}^{J} \lambda_j = 1, j = 1, \ldots J$$

$$\lambda_j \geq 0$$

The *j*-th DMU is radially efficient, assuming that the optimal values of its efficiency ratio, θ_j, equal unity, but there can be further improvement in the efficiency when there is any mix inefficiency connected with non-zero input and output slacks. *Source*: Cooper, Seiford, and Tone (2006).