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WHEN DOES ADVERTISING HAVE AN IMPACT? A STUDY OF TRACKING DATA

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This paper attempts to find characteristics of product categories, brands, and ad copy that lead to either increased or decreased effectiveness of advertising spending on ad awareness, brand awareness, or purchase intentions, as measured through tracking data. Using a meta-analysis of such data for frequently purchased packaged goods, we find that advertising spending has a greater effect on awareness for less-visible brands in growing product categories and a greater effect on purchase intentions when the ad features a new strategy or new copy or new benefits; when the brand has significant trade promotion support; when the ad copy is not "soft sell"; and when the brand is not already a "declining brand." These results are generally consistent with earlier field studies examining the effects of advertising weight on sales.

Recent years have seen great interest, both academic and managerial, in the issue of whether advertising has any appreciable impact on short-term sales and—if it does—the types of situations that magnify or attenuate this impact. Academic studies have been published that argue that the direct short-term sales effect of advertising is, in general, quite low (Aaker and Carman, 1982; Assmus, Farley, and Lehmann, 1984; Tellis, 1988). Some published industry tests of increased advertising spending, using "single-source" data, have found that increased advertising leads to short-term sales increases (in the current week) about 70 percent of the time, with these increases being modest or better only 50 percent of the time (Jones, 1995a, 1995b). Other industry studies have also found that advertising pays off only in limited situations, such as in the case of new/small brands or, for old/large brands, only when new marketing strategies, new copy, or new reach-maximizing media plans are used (Eastlack and Rao [1986, 1989] on the Campbell Soup Co. tests; Lodish et al. [1995] and Lubetkin [1992] on the IRI tests). Taken together, these recent results support the earlier finding of generally decreasing (concave) returns to increased advertising spending or exposures (Simon and Arndt, 1980).

However, while these studies support the belief that mass media advertising has a limited ability to increase short-term sales, they also raise the question of whether the same pattern of low/diminishing/situationally contingent returns also exist for other marketing variables that are influenced by advertising. Two sets of such variables are relevant here. There are first the cluster of brand awareness, attitudes, purchase intent, and quality beliefs that are frequently called "brand equity" or brand "goodwill" (Aaker, 1991; Keller, 1993). A case could well be made that while advertising has only a limited short-term sales impact, it may have a bigger (but less easily quantifiable) effect on such "equity" variables, which in turn lead to long-run sales. On the other hand, it is also possible to conceive of ads that increase short-term sales but damage longer-term brand equity. In fact, Jones (1995a, 1995b) reported that while 70 percent of ad campaigns are effective in the current week, only 46 percent sustain that success over the course of a year. This difference in short-term versus long-term results suggest that it is clearly desirable to also examine the impact of advertising spending on variables other than short-term sales.

Second, there are the various "intermediate communication variables," such as ad and brand awareness and brand beliefs, attitudes, and intent, that are argued to be "purer" measures of an ad's communication effectiveness than are sales measures because they are not influenced (as are sales) by other marketing-mix inputs and exogenous events (Colley, 1961). Since the Campbell Soup, Jones, and IRI studies cited earlier measured advertising effects under experimental conditions (and/or used single-source data) that controlled for (or covaried out) other marketing-mix inputs, their sales measures effects should be a valid measure of ad effectiveness when such experimentally-controlled sales data are available. However, experimental and/or single-source data are expensive and limited, so that many studies of advertising effectiveness on sales are forced to use nonexperimental regression-type models that only incompletely control for these other marketing-mix influences. Since tracking data on the "intermediate variables" are frequently collected by agencies and advertisers, and since they may be "purer" measures of advertising effect than incompletely controlled sales effect measures, it is clearly worthwhile to see if advertising effects on "intermediate" tracking data are consistent with advertising effects on well-controlled sales data. If this is found to be the case, models created on "intermediate" tracking data could be created that have ready and ongoing usefulness.

While there have previously been scattered reports in the published literature that have quantified the effects of advertising on awareness, attitudes, etc., under field conditions (e.g., Geiger, 1971; Time/Seagram, 1982), such studies have typically been limited to one or very few brands and product categories, making it difficult to draw conclusions about the factors that *moderate* (magnify or reduce) the effects of advertising on such variables (such as new versus old brand, new versus old copy strategy, etc.). Studies of moderating variables can obviously be done only if there is enough variance, in the data, across these potentially moderating variables.

It would therefore seem potentially very useful to be able to do the kinds of meta-analyses reported by Assmus, Farley, and Lehmann (1984) or Lodish et al. (1995) on dependent variables other than short-term sales, by identifying the factors that magnify or attenuate the impact of advertising and using a database that provides adequate variation across potentially moderating variables. This paper reports such an analysis. Using a unique and comprehensive "tracking" data base developed by an advertising agency, it explores the factors that appear to moderate the effects of advertising spending (GRPs) on ad and brand awareness and on brand purchase intent. Many of the independent or moderating variables are similar to those used in the Campbell Soup, IRI, and Nielsen analyses, allowing for a comparison of findings.

Literature Review and Hypotheses

Since our main focus in this study is an investigation of the factors that appear to moderate the effects of advertising spending, rather than its "main effect," we limit this review to reports of these interacting factors. Most of these studies are "lab" studies, investigating the effects on various dependent measures of variations in exposure frequency. For example, Batra and Ray (1986) found that higher levels of advertising exposure led to increasing levels of brand attitudes and purchase intentions when the product categories were such that consumers were less motivated to process ad message arguments (so-called "low involvement" situations), because more motivated consumers "absorbed" the ad message more quickly, reducing the need for further exposures. Other lab studies have found that heavier levels of repetition can be more profitably employed when the consumer is more familiar with or loyal to the brand (Raj, 1982); when the ad message is more complex (Anand and Sternthal, 1990); when there is more competitive spending (Burke and Srull, 1988) and more advertising clutter (Webb and Ray, 1979); etc. (See Ostrow [1984] and Pechman and Stewart [1988] for extensive reviews of this prior work.)

Among studies using "field" data, similar to the data used in this study, Tellis (1988) found advertising's effect on sales (brand choice) to be stronger among consumers already loyal to the brand, i.e., a strong "reinforcement" effect, than in winning new buyers for new brands. Aaker and Carman (1982), reviewing the results from AdTel split-cable studies of changes in advertising weight and copy conducted during the 1970s, reported that while only 30 percent of the "weight" tests showed significant differences, 47 percent of the copy tests did, suggesting that changes in advertising copy were more likely to lead to sales gains than changes in media weight alone. Assmus, Farley, and Lehmann (1984), in a meta-analysis of the published econometric literature (n = 128 models), found that food products had elasticities of sales response to advertising that were higher than the mean, while elasticities in Europe were (at that time) higher than those in the United States.

The three sets of previous studies that are of most relevance to the present research come from 19 field experiments carried out by Campbell Soup during the mid 1970s (Eastlack and Rao, 1986, 1989), an analysis by IRI of the results of 389 split-cable tests conducted during 1982–1988 (Lodish et al., 1995), and analysis of Nielsen "single-source" data by Jones (1995a, 1995b) using scanner data collected during 1991–1992.

In the Campbell Soup tests, the company found that for the well-established, mature brands tested, short-term sales effects of increased ad expenditures (measured through SAMI warehouse withdrawals) were significant only when the advertising tested new copy or a new strategy, or when a new media mix was employed that attempted to increase reach by targeting new audiences or utilizing different media or day-parts. In their words, "consumers did not respond to being told the same thing more often" (Eastlack and Rao, 1989). Very relevant to the present study, they report that their tracking data on awareness, trial, and usage did not tend to correlate with the sales results seen, though attitude shifts tracked did appear to be more correlated with the observed sales changes.

The IRI analysis of 389 split-cable advertising experiments (Lodish et al., 1995; Lubetkin, 1992) also comes from the packaged-goods domain and included 217 weight tests for established brands, 76 weight tests for new brands, and 86 copy tests for established brands. To summarize, these tests too found that there was no simple relationship between the size of the increase in television advertising spending weight and the increase in sales and/or market share. Instead, they found (among other results) that higher advertising spending was more likely to lead to higher sales when:

1. There was a change in brand or copy strategy, and the copy strategy aimed at changing rather than reinforcing old attitudes.
2. Media plans attempted additional reach and/or used relatively less prime-time.
3. The product category was growing, and/or the number of purchases per buyer was high.
4. The brand was newer (had less prior awareness) or was smaller/medium-sized.
5. Higher levels of consumer couponing existed.
6. The brand had lower levels of trade dealing (in-store displays, store coupons, etc.).

These were some of the 350 independent category, brand, copy, and media variables that proved to be significant predictors of obtained sales changes at the 80 percent level of significance. Some of their results not pertinent to the present study are omitted here. Importantly, weak or nonexistent relationships were found, in the aggregate, between standard recall (normalized) copytest scores and sales effects, or standard persuasion (normalized) copytest scores and sales effects, unless those scores were at extremes. No tests were reported of relationships between the sales changes found and tracking data on awareness, attitudes, or intentions.

The study of Nielsen single-source data by Jones (1995a, 1995b; see also Ephron, 1995, and Reichel, 1994) is based on data collected from 2,000 households in 1991–1992 on 78 TV-advertised brands in 12 product categories. Jones finds, based on a "quintile analysis," that the key characteristics of the most successful ad campaigns are that they are creatively effective (1995a) and that they are for brands that command a higher-than-average price (1995a). Jones also reports very high synergies between advertising intensity and promotions (1995a). Finally, Jones (1995b) finds support for the superiority of media strategies that emphasize reach over frequency, because the first exposure (in the week-before-purchase) provides the biggest effect, with further exposures adding very little. Ephron (1995) and Reichel (1994) provide further support for the superiority of such reach-enhancing media strategies, also using Nielsen single-source data.

The consistency of results among the three sets of studies is remarkable. Both the Campbell Soup and IRI studies point to the importance, for increasing sales, of having new brand or copy strategies and/or new media (reach-enhancing) strategies. The Nielsen (Jones) studies also support the importance of creatively-superior copy and of reach-enhancing media strategies. The IRI studies, in addition, point to the facilitating role of category growth, and of consumer promotions, in moderating the effect of advertising weight on sales.

While these empirical results may appear to be somewhat "ad hoc" and atheoretical, most of them are, in fact, consistent with a conceptual framework in which increased advertising spending pays off only to the extent that there is further "room" for it to have an effect. In other words, increased advertising spending could logically be expected to result in measurable effects (on sales, attitudes, intent, etc.) only if prior levels of consumer knowledge about the brand were not already as high as they could be. Such consumer knowledge levels would be at already very high levels if the brand was already extremely well-known, or was an old/mature brand, or had high consumer penetration or very high market share, or had very high prior ad support levels. Conversely, such existing consumer knowledge would be at relatively low levels if the consumer was new to the category and/or the brand, either because the category was growing fast or because the brand was new or relatively less known, or because this consumer had not been exposed to the media that traditionally carried that brand's advertising. Consumer knowledge would also have more room to be affected by advertising if the message in the ad was substantially different from that communicated in earlier ads; if not, the ad would only be attempting to communicate something already known by the consumer, leading to no measurable change. In sum, such a conceptual framework could explain most of the results found in the Campbell Soup, IRI, and Nielsen results, and we could logically use it to anticipate results in the present data set.

As mentioned, the distinctive feature of this present data set is the availability of data on advertising weight effects, not on short-term sales, but on tracking data on ad and brand awareness and brand purchase intent. The obvious question in developing our hypotheses is whether we should expect the effects of ad weight on our tracked variables to parallel the effects found on short-term sales.

Using the conceptual framework just suggested, we should expect increased advertising weight to lead to increases in these tracking communication measures of ad awareness, brand awareness, and purchase intent more when existing consumer knowledge of that ad's message was relatively low, e.g., for changed ad strategy or new copy, for newer brands, for faster growing product categories drawing in newer consumers, for situations where prior ad support levels were relatively low, etc. There are several reasons, however, why this "overall" expectation may not apply to our three tracking variables equally. Note that, as mentioned earlier, the Campbell Soup studies (Eastlack and Rao, 1989) found that their ad (weight and copy) effects on sales were paralleled somewhat by effects on brand attitudes but not by effects on brand awareness. This might seem to suggest that in our data such ad effects should emerge most clearly on our brand purchase intent variable, since that is conceptually closer to brand attitudes (and to actual sales) than either of our awareness variables.

However, there are several reasons why this may not happen. First, the Campbell Soup results (of no ad effects on tracked brand awareness) may simply be due to "ceiling effects": for their tested brands, prior brand awareness may simply have been at such high levels that further increases were close to impossible, while sales levels still had "room to grow" (e.g., through increases in per capita consumption among already-aware consumers) and thus did so. It is possible that these particular results may be hard to generalize to less well-known brands.

Second, the hierarchy-of-effects model suggested by Colley (1961) and others would indicate that ad effects should lead first to increases in ad awareness, which should precede any effects on brand awareness, which themselves should then lead to any changes in brand purchase intent. This would then suggest that any increases in ad weight should be felt most strongly on ad awareness (the first step among our three dependent variables), next most strongly on brand awareness (the second "step" in our set of variables), and least strongly on purchase intent (the final "step"). Ad effects on ad awareness should also be greater than effects on brand awareness, because the latter should be more stable and less volatile than the former, since brand awareness also depends on other marketing factors like distribution. Indeed, using the "hierarchy-of-effects" idea that effects on a lower "step" of the hierarchy must be preceded by effects on earlier steps, it might even be argued that increased ad weight would

Table 1
Moderating Variables Available in Data Set

A. Product category characteristics	
1.	Category penetration (<20%/20–50%/50–80%/80%+)
2.	Category life-cycle stage (new/growing/mature/declining)
3.	Category annual growth rate (decline/<5%/5–10%/10–25%/>25%)
4.	Number of purchases per year
B. Brand characteristics	
5.	Brand life-cycle stage (new/growing/mature/declining)
6.	Brand annual growth rate (decline/<5%/5–10%/10–25%/>25%)
7.	Relative market share (low/below average/average/above average/high)
8.	Relative price (low/below average/average/above average/high)
9.	Relative advertising level (low/below average/average/above average/high)
10.	Relative promotion support (low/below average/average/above average/high)
11.	Relative quality reputation (low/below average/average/above average/high)
C. Advertising characteristics	
12.	Use of image in copy (yes/no)
13.	Use of humor in copy (yes/no)
14.	Use of emotion in copy (yes/no)
15.	Use of product benefits in copy (yes/no)
16.	Use of product demonstrations in copy (yes/no)
17.	Use of technical facts in copy (yes/no)
18.	Use of comparative techniques in copy (yes/no)
19.	Was a new use or benefit highlighted (yes/no)
20.	Was the copy new/old
21.	Was the strategy new/old
D. Sales promotion characteristics	
22.	Use of money-off coupons (yes/no)
23.	Use of product sampling (yes/no)
24.	Use of in-store display (yes/no)
25.	Use of direct mail (yes/no)
26.	Use of trade promotions (yes/no)

have no effects on purchase intentions if ad and brand awareness were not already at high levels.

Third, as pointed out by the marketing consultancy Millward-Brown, the tracked awareness measures may well be consequences of actual sales, rather than predictors of it in the hierarchy-of-effects sense just discussed. To quote: "The brands that come most readily to people's minds are the ones they've recently bought!" (Brown, n.d.). These arguments too suggest that ad effects on both brand and ad awareness should thus also correlate highly with effects on sales, albeit not for the hierarchy-of-effects reason just discussed.

Finally, for packaged goods such as the ones in our data set, advertising-induced changes in ad and brand awareness could both be expected to correlate highly with eventual changes in sales, and thus track the Campbell Soup/IRI/Nielsen results on sales, because (inadequate) distribution and (too-high) price are unlikely to be barriers to purchase. The correlation between brand recall and purchase intent is usually high for low-involvement goods such as these (Beattie and Mitchell, 1983), so that the same factors that moderate ad-weight effects on sales should also moderate ad-weight effects on ad and brand awareness.

For these reasons, we take as our working hypothesis the expectation that the *moderating factors* that proved significant in the Campbell Soup, IRI, and Nielsen data, on sales effects, will also prove to be significant moderators of ad-weight effects on ad and brand awareness and purchase intent in our tracking data. However, since advertising effects are probably most directly related to our measures of ad awareness, next closest to brand awareness, and least close to purchase intentions, we expect the *main effect* of advertising to be strongest for ad awareness data, less so for brand awareness data, and least for purchase intentions data.

Data and Method

The data for this study were collected by the Media Research Group at the Foote, Cone and Belding advertising agency (now called True North Communications) in New York, from their archived data on campaigns run during the late 1980s and early 1990s. For each campaign, tracking data on various measures had been collected, usually from ongoing telephone interviews with target consumers (such as female heads of household/primary grocery shopper), using national probability samples. The period of these data varied across cases (in some cases they were quarterly, in others monthly or weekly). These served as the dependent variables in the analysis. Reach and Frequency data, and thus Gross Ratings Points (GRP) data, were also collected for matching time periods, by individual medium (these were aggregated across all media in the analysis, without any weighting). This served as the main predictor variable. The agency person(s) involved with each campaign also filled out a questionnaire providing data on the product category, brand, brand ad campaign, and concurrent promotional campaigns, which served as potential moderator variables. A listing of these is provided in Table 1.

Data were obtained for a total of 29 separate campaigns, with each campaign providing between 2 and 25 observations, some for multiple target audiences. (For example, one subset of the data covered a campaign for confectionery products, with quarterly tracking data from each of two teen and adult target markets, from the second quarter of 1989 to the first quarter of 1992.) From these data, a set of matched observations was created using every pair of adjacent time periods: e.g., the ad awareness of the third quarter of 1989 (time period "*t*") was paired for modeling purposes with the GRPs for that same time period *t*, the ad awareness in the prior second quarter (time period *t*-1), and the coded moderating variables (which did not change across time periods). This led to a total set of 230 such "matched" observations. It should be apparent that these were not 230 technically independent observations, since several of them came from the same set of product/campaign/year factors. Thus their use in the OLS regressions reported below as if they were independent observations does constitute a technical limitation, to be discussed later.

Since the data available for each campaign often covered different dependent and moderating variables, leading to large amounts of missing data, the analysis below was restricted to that subset of the data and those variables where enough data existed to allow analysis. Usable data were available for 224 observations for ad awareness, 230 for brand awareness, and 159 for purchase intentions, before a few outliers were excluded (described below). The dependent variables were ad awareness, brand awareness, or brand purchase intent, in time period $t+1$. The independent variables and moderating variables will be discussed below.

1. Outlier Exclusion. The distribution of each variable potentially usable in the analysis was checked, through histograms, stem-and-leaf plots, and normal probability plots. The cases that were causing outliers (observations more than 2 standard deviations from the mean) were iteratively deleted, starting with the most severe offenders first. It was discovered that the nine most problematic cases could be deleted by applying the rule that cases should be limited to those where the year-to-year percentage change in the reported levels of brand awareness, ad awareness, brand purchase intentions, and media GRPs were each less than 200 percent above their previous-year levels. In other words, outliers tended to come from those cases where one or more of these variables changed by more than 200 percent from their year-ago levels, and these cases were excluded. Another 3 cases were excluded because they came from Europe, thus limiting the final 218 cases to United States data only. In sum, 12 cases (5 percent) of the original usable cases were excluded from the cases either because they represented extreme levels of change (200 percent+) in key variables, or because they came from an isolated set of non-U.S. data, leaving 218 cases for brand awareness, 213 for ad awareness, and 147 for purchase intentions.

2. Descriptive Statistics. Selected descriptive statistics of the data set (after outlier removal) are presented in Table 2. The average level of base period ad awareness of the brands in the sample was about 34 percent (range: 2 percent to 96 percent), of brand awareness 85 percent (range: 22 percent to 100 percent), and of purchase intentions 29 percent (range: 3 percent to 75 percent). The level of GRPs per four-week tracking period averaged about 500 (ranging from 0 to 3612). The change in ad awareness averaged +0.16 percentage points (range: −31 percentage points to +31 percentage points). For brand awareness the change averaged +0.18 percentage points (range: −20 percentage points to +20 percentage points), while for purchase intentions there was essentially no increase on average, though the change ranged from −14 percentage points to +18 percentage points.

A "profile" of our data set, in terms of the potential moderator (category, brand, ad execution, and promotion support) characteristics, is also in Table 2. Our data typically came from frequently purchased products, in categories that are mature and slow-growing, with high category penetration rates. Only about a third of the brands were new or still in their growth stages. Most had average price but above average quality, with relatively stronger promotion support than advertising support. The ad executions used tended to rely more on image (76 percent) than on product demonstration (17 percent) or a comparative format (22 percent). About half used a new ad strategy and/or new ad copy. Promotional support tended to consist mostly of trade promotions (used by 84 percent), product sampling (used by 80 percent), and money-off coupons (used by 59 percent).

3. Analysis Overview. Our concern in this study is the identification and statistical testing of *interactions:* variables that either magnify or reduce the effect of advertising spending (measured via GRPs) on the three dependent variables of interest (cur-

Table 2
Descriptive Statistics of Sample after Outlier Removal

Tracking data	*N*	Mean	Standard deviation
Ad awareness in year 0	214	34.36%	20.06%
year 1	213	34.38%	20.48%
Brand awareness in year 0	218	85.18%	16.71%
in year 1	218	85.27%	16.40%
Purchase intentions in year 0	148	29.29%	18.47%
year 1	147	29.24%	18.67%
GRPs in year 0	218	530.95	582.40
year 1	218	461.59	496.94

*Category characteristics**	
Category penetration	67% of cases between 50–80%, 30% of cases above 80%
Category life cycle	41% "growing," 50% "mature"
Category annual growth rate	87% of cases growing <5% per year
Number of purchases/year	mean = 55 (standard deviation: 86)
Brand characteristics	
Brand life cycle	20% "new," 14% "growing," 47% "mature," 19% "declining"
Brand annual growth rate	47% "declining," 46% growing <5% p.a., 8% growing at >5% p.a.
(Relative) market share	32% "low"/"below average," 40% "average"/"above average," 38% "high"
(Relative) price	79% "average," 17% "above average"
(Relative) ad support	49% "below average," 25% "average," 25% "above average"/"high"
(Relative) promotion support	35% "below average," 38% "average," 27% "above average"/"high"
(Relative) quality reputation	24% "average," 48% "above average," 26% "high"
Ad characteristics	
Use of: Image	76%
Humor	49%
Emotion	33%
Product benefit	81%
Product demonstration	17%
Technical details	1%
Comparative	22%
New use/benefit	41%
New copy	51%
New strategy	48%
Promotion characteristics	
Use of: Money-off coupons	59%
Product sampling	80%
In-store display	12%
Direct mail	6%
Trade promotions	84%

* Totals may not sum to 100% because the complete frequency distribution is not reported here for brevity.

rent period ad and brand awareness and purchase intentions). The regression models to be estimated therefore include as independent variables (a) current period GRPs, (b) the main effects of these moderator (interaction) variables, (c) the interactions of these moderator variables with GRPs, and (d) the lagged dependent variable, measuring carryover effects. We used as the dependent variable the logit of ad, brand, or purchase intentions. (The logit of any dependent variable expressed as a percentage [e.g., of percent ad awareness] is computed as the natural log of [percent ad awareness/(1 − percent ad awareness)].) This transformation of the dependent variable adjusts for ceiling effects. It also has the advantage that, unlike the untransformed awareness or intentions dependent variable, it is constrained to a maximum of 100 percent and is therefore logically consistent.

Correlations among our moderator category/brand/ad/promotion variables were high enough to be potential sources of multicollinearity in such a model. For instance, product category penetration correlated 0.58 with category life cycle stage, high brand market share correlated 0.72 with high brand promotional support, and the presence of image in the ad execution correlated −0.54 with the use of a comparative claim—while raw GRPs correlated only in the 0.05 to 0.33 range with the dependent variables. Because such multicollinearity would make it difficult to obtain significant coefficient estimates using the model above, several collinearity-reducing changes were made prior to obtaining our regression estimates.

First, instead of using each moderator variable as a separate independent variable (with its own interaction term with ad spending), we create and use principal components based on those moderator variables, where each principal component is orthogonal (unrelated) to each other and thus does not suffer from multicollinearity.

Second, we use these principal components (created from the moderator variables) to cluster our cases (observations) into homogenous subsets of advertising situations sharing the same levels of the principal components. In other words, our data set of product categories, brands, and ad campaigns was broken up into smaller clusters or groups, each group being internally similar on those moderator variables, with the different groups differing maximally on those moderator variables. Thus one cluster might potentially consist of newer brands in younger product categories with newer ad messages, while another might potentially consist of older brands in mature categories that are simply repeating old copy. Dummy variables for these clusters (and their interactions) were then used as the independent variables in our regression model. This approach allows the naturally occurring pattern of relationships that exist in the data (e.g., new ad strategy and copy are more likely from newer brands in growing categories) to be used in the model, without creating artificially orthogonal constructs while also reducing multicollinearity. This approach is recommended by Farley and Lehmann (1986).

Third, since each main effect in the model is highly collinear with its interaction with GRPs, making interpretation of main effects problematic, we obtain our model estimates not on the raw independent variable (cluster dummy variable) data but instead on mean-centered data. That is, each of the independent cluster dummy variables was first rescaled to a mean of zero before its interactions with GRPs was computed. As pointed out by Ross and Creyer (1993), the coefficients estimated for the main effects are interpretable when such mean-centered data are used but not if the raw data are used.

Our final modification was made not to reduce collinearity but to allow for the effects of advertising GRPs on the tracked dependent variables to be *nonlinear*. It is well known that the effects of advertising on various measures have most frequently been found to fit a downward concave (decreasing returns) function (Simon and Arndt, 1980). We therefore checked to see if the relationship between the current period awareness/intentions measures and current period advertising GRPs went up if those GRPs were transformed to either their natural log or their square root. We found substantial increases when the square-root transformation was used. As a consequence, GRPs were used in the model after a square-root transformation, and the interaction terms for the dummy variables were created by multiplying the mean-centered dummy variables with the square root of GRPs.

To summarize, the regression models estimated below were of the following form: Logit of the current-period dependent variable (ad awareness/brand awareness/purchase intentions) as a function of:

1. square root of current period advertising GRPs
2. the dependent variable one time-period ago
3. dummy variables for the cluster into which each case (observation) fell, these clusters being based on principal components of the moderator

variables (each dummy variable being mean-centered), and

4. interaction terms of each mean-centered cluster dummy variable times the square root of current period advertising GRPs

4. Analysis of Moderator Variables. All moderator variables available in the data set were used in a principal components analysis, except for four that had a relatively high number of missing values. The 22 moderator variables yielded a scree pattern in which the first 8 components had gradually declining eigen values greater than 0.99, followed by a drop to 0.87; these 8 components were thus retained, cumulatively explaining 85 percent of the variance. The varimax-rotated loadings for these eight components are reproduced in Table 3.

Table 3 shows that the first component consists of the ad strategy being old, the brand being a mature/declining brand, the ad copy being old, and the ad copy being comparative. It is negatively related to the ad copy being image-oriented (so the ad is not image oriented) and the ad copy showing a new use or benefit (so the ad copy is not showing a new use or benefit). We therefore call this first component "Old News."

The second component is positively related to the ad copy being emotional and using humor and, less strongly, on emphasizing image. It loads negatively on the ad copy featuring product benefits (so the ad copy does not emphasize product benefits). We call this second component "Soft Sell."

The third component relates positively to the brand using in-store displays, the ad copy using

Table 3
Principal Components Loadings (Varimax-Rotated)

	1	2	3	4	5	6	7	8
Ad strategy = old	0.83	−0.06	0.17	0.03	−0.23	−0.12	−0.04	−0.19
Brand = mature/declining	0.81	0.19	0.05	0.20	0.22	−0.10	0.02	0.27
Ad copy = old	0.77	0.41	−0.17	−0.19	−0.17	−0.16	0.07	−0.05
Ad copy = comparative	0.66	−0.38	0.11	−0.30	0.04	0.10	0.47	0.11
Ad copy = image	−0.61	0.49	0.07	0.10	−0.28	−0.26	−0.02	0.12
Ad copy = new use	−0.79	−0.36	0.13	0.12	0.05	0.00	0.35	0.18
Ad copy = emotional	0.19	0.77	0.06	0.03	−0.26	−0.14	−0.27	0.05
Ad copy = humorous	0.07	0.68	−0.08	0.60	0.16	0.08	−0.00	−0.08
Ad copy = product benefits	−0.11	−0.89	0.08	0.29	−0.23	−0.09	−0.02	0.00
Promotions = in-store display	0.05	0.08	0.81	−0.00	0.02	−0.01	0.13	0.31
Ad copy = demonstration	0.07	−0.12	0.76	0.06	0.19	0.02	−0.22	−0.08
Price = high	−0.07	0.02	0.65	−0.17	−0.29	0.37	0.37	0.18
Promotions = sampling	−0.07	0.05	−0.79	0.12	0.04	0.27	−0.26	−0.09
High purchase frequency	−0.04	0.06	−0.30	0.88	−0.20	−0.04	−0.02	0.07
Category = mature/declining	−0.03	−0.10	0.44	0.71	0.04	−0.20	−0.07	−0.18
Brand = high quality	0.15	0.47	0.12	−0.65	0.18	0.28	−0.07	−0.35
Promotions = trade promotions	0.01	−0.03	0.13	−0.22	0.91	−0.09	0.08	0.05
Promotions = coupons	0.31	−0.45	0.29	−0.28	−0.60	−0.15	−0.19	0.16
Category = high growth	−0.30	−0.11	0.00	−0.01	0.09	0.82	−0.10	−0.01
Category = high penetration	−0.22	−0.15	0.19	0.39	0.25	−0.74	−0.04	0.11
Promotion = direct mail	−0.05	−0.12	0.20	0.00	0.03	−0.09	0.83	−0.17
Ad copy = technical	0.08	−0.02	0.28	0.01	0.01	−0.06	−0.15	0.82

product demonstrations, and the brand being relatively high priced. It loads negatively and strongly on the brand using sampling (so no sampling is being used). This component is not easy to describe, but we label it "Visibility."

The fourth component is positively related to the ad copy using humor, the purchase frequency being high, and on the product category being in its mature or declining life-cycle stage. It relates negatively to the level of relative brand quality (so brand quality is relatively low). We label this component "Declining Brand."

The fifth component is positively related to the use of trade promotions and negatively to the use of coupon promotions. We call this component "Emphasis on Trade Promotions."

The sixth component is positively related to product-category growth and negatively to category penetration. We call this component "Growing Category."

The seventh component is positively related to the use of direct mail and also to the ad copy being comparative. We call this component "Hard Sell."

The eighth and final component is positively related to the ad copy being technical. We call this component "Technical Copy."

5. Clustering Results. Principal component scores were computed for each of the eight components for each observation in the data set and were then standardized to a mean of zero and a standard deviation of 1. K-means clustering analysis (implemented through the SAS procedure FASTCLUS) was then used to cluster the 218 observations, on the basis of the standardized principal component scores. Cluster solutions were obtained for two through eight clusters and the resulting statistics (pseudo-*F* statistic, approximate overall *R*-squared, and cubic clustering criterion) compared across the different solutions. The comparison suggested using the seven-cluster solution, because it yielded the highest values for the three statistics. Two of the seven clusters were large ($n = 113$ and $n = 53$), two were small ($n = 20$ and $n = 19$), while three were essentially trivial (n's $= 7$ or under).

A "profile" of the means of the seven clusters on the eight standardized principal component scores is provided in Table 4. For brevity, this discussion limits itself to the four "nontrivial" clusters (numbers 3, 4, 5, and 7).

The brands and campaigns in Cluster 3 appear to be above average on the first component ("old news"), the second component ("soft sell"), and on the fourth component ("declining brand"). They appear to be well below average on the fifth component ("emphasis on trade promotions"), implying the brands are not being supported by high trade promotions. We call this cluster of brands/campaigns "No news/no trade promotions."

The brands and campaigns in Cluster 4 appear to be above average on both the second ("soft sell") and third components ("visibility"). We call this cluster of brands/campaigns "Visible/soft sell."

The brands and campaigns in the biggest cluster, Cluster 5, are

Table 4
Cluster Scores on Standardized Principle Components

		Principal component							
		1	2	3	4	5	6	7	8
Cluster	*n*	"Old" News	"Soft Sell"	"Visibility"	"Declining Brand"	"Emphasis on TP"	"Growing Category"	"Hard Sell"	"Technical Copy"
1	3	−0.26	−0.53	0.99	−0.40	−0.25	4.91	3.77	−0.17
2	7	0.08	−0.54	−0.06	−0.30	−0.15	−3.02	3.42	−0.75
3	19	0.73	0.47	−0.43	1.61	−2.20	0.07	−0.39	−0.09
4	20	0.32	0.40	2.20	−0.04	0.06	0.22	0.67	−0.06
5	113	−0.02	0.07	−0.53	−0.69	0.06	0.19	−0.16	0.02
6	3	−0.71	−0.18	2.32	0.09	0.07	−0.49	−1.28	6.96
7	53	−0.31	−0.37	0.28	0.96	0.68	−0.35	−0.36	−0.27

not surprisingly pretty average. They are low on the third "visibility" component and most negative on the fifth "declining brand" component. Thus these are relatively high-quality brands in new/growing categories that, at least for now, are not yet salient and visible. We call this cluster of brands/campaigns "Emergers."

Our last major cluster, Cluster 7, has brands and campaigns that are noticeable most for their above-average level of trade promotions (component 5), though they are also relatively high on the 4th "declining brand" component (mature categories, parity equality, etc.). We call this cluster "Promoted life-support."

6. Prediction of Awareness and Intentions. OLS regression estimates were obtained for models in which the logit of the dependent variable (ad awareness, brand awareness, or purchase intentions) in the current time period "t" depended on that same variable in the prior time period "t-1"; the square-root of GRPs in that same time-period; the dummy variables for clusters 3, 4, 5, and 7; and the interaction term of the square-root of same-period advertising GRPs times the cluster dummy for clusters 3, 4, 5, and 7. The data for the dummy variables were mean-centered before these dummy variables, and their interaction terms with the square-roots of GRPs, were created. The few observations from the three trivial-sized clusters (1, 2, and 6) were omitted both because their estimates would be unstable and because at least one cluster has to be dropped to allow the model to be estimated.

The results, presented in Table 5, provide both the unstandardized and standardized coefficient estimates. Many previous field studies of advertising effectiveness (e.g., Haley and Baldinger, 1991; Lodish et al., 1995) have only found significant effects at $p < .20$, so this seemingly loose level of significance should be considered a reasonable one here. Note that a significant coefficient for a dummy variable for a cluster merely means that the particular dependent variable tends to be higher for brands/campaigns in that situation. What is of interest to this study is the significance of the interaction terms, which imply that higher advertising weight has a differential effect (higher or lower, depending on the sign) on that dependent variable for brands/campaigns falling into that cluster.

Ad Awareness. The results show first that carryover effects,

Table 5
OLS Regression Results

	Logit of Ad Awareness$_t$	Logit of Brand Awareness$_t$	Logit of Purchase Intentions$_t$
n	212	205	146
R^2	0.826	0.797	0.910
Intercept	−2.14 (0.00)	−2.98 (0.00)	−2.24 (0.00)
Dependent variable in last time period	0.04 (0.82)*	0.06 (0.78)*	0.04 (0.79)*
Square-root of GRPs in this time-period	0.01 (0.15)*	0.02 (0.17)*	0.00 (0.01)
Square-root of GRPs* Cluster 3	−0.00 (−0.00)	0.02 (0.06)	−0.02 (−0.13)****
Cluster 3 dummy (No news/No TP)	−0.20 (−0.06)	−0.07 (−0.01)	0.09 (0.03)
Square-root of GRPs* Cluster 4	0.02 (0.05)	0.00 (0.01)	−0.03 (−0.08)***
Cluster 4 dummy (Visible/soft sell)	0.02 (0.01)	0.34 (0.07)****	0.61 (0.14)*
Square-root of GRPs* Cluster 5	0.02 (0.11)****	0.05 (0.21)**	−0.01 (−0.08)
Cluster 5 dummy (Emergers)	0.03 (0.01)	0.41 (0.15)***	0.45 (0.23)**
Square-root of GRPs* Cluster 7	0.01 (0.02)	0.01 (0.03)	−0.03 (−0.18)**
Cluster 7 dummy (Promoted Life Support)	−0.21 (−0.09)****	0.13 (0.04)	0.22 (0.10)

Standardized Coefficients in parentheses.
* $p < .01$
** $p < .05$
*** $p < .10$
**** $p < .20$

and the main effect of advertising weight, are both highly significant ($p < .01$). We see next that ad awareness tends to be higher in general (i.e., a significant "main effect" exists) for cluster 7, brands that are highly trade-promoted. This could either be because highly trade-promoted brands are already high awareness brands, or because the trade promotions draw consumer attention to these brands' ads. More importantly, advertising weight effects on ad awareness are higher for cluster 5 brands ($p < .20$). This cluster consists of brands that are of relatively high quality, in new/growing product categories, and that do not already have a high level of "visibility," what we earlier called "Emergers."

Brand Awareness. The results again show first that carryover effects, and the main effect of advertising weight, are both highly significant ($p < .01$). The clusters that have a significant "main effect" here are clusters 4 ($p < .20$) and cluster 5 ($p < .10$). This implies that brand awareness tends to be higher in general for brands that are either "Visible/soft sell" of the "Emergers" (as for ad awareness). More importantly for our purposes, a significant interaction between cluster membership and ad weight emerges only for cluster 5 (at $p < .05$), the "Emergers." As for ad awareness, it appears that ad weight has a greater effect on brand awareness for brands that are of relatively high quality, in new/growing product categories, and that do not already have a high level of "visibility," our so-called "Emergers."

Purchase Intentions. For intentions, while carryover effects are again significant ($p < .01$), there is no statistically significant main effect of ad spending. We do, however, find three statistically significant interactions of ad spending weight with cluster membership.

First, it appears that ad weight appears to have a significantly lower effect on purchase intentions for cluster 3, the "no news/no trade promotions" cluster ($p < .20$). By implication, this means that ad weight effects on purchase intentions are significantly higher when there *is* "news" (such as a new ad strategy, new ad copy, or ad copy showing new benefits or uses) and/or when there is trade support.

Second, it appears that ad weight has a significantly lower effect on purchase intentions for cluster 4, the "Visible/soft sell" cluster ($p < .10$). By implication, this means that ad weight effects on purchase intentions are significantly higher when the ad copy is *not* "soft sell"—oriented toward image, emotion, or humor—but instead focuses more on product benefits (which provide a specific reason for buying). Further, these effects are higher when a brand does not already have high in-store displays, does use sampling, and is not relatively high priced.

Finally, ad weight effects on intentions appear to be significantly lower for cluster 7 ($p < .05$). These are the "declining brands" (mature categories, parity quality) getting high trade promotion support. It appears that increasing ad spending is relatively ineffective for such brands.

Discussion

In summary, our results show both similarities and differences with the earlier results found in the Campbell Soup, IRI, and Nielsen studies. In terms of similarities, we too find a strong and significant increase in the effect of advertising when the product category is new or growing. This effect emerges for our dependent measures of tracked ad and brand awareness. Also like those earlier studies, we too find that a new ad strategy or new copy or ad copy stressing new uses of benefits magnifies the effect of higher ad weight, though this result emerges in our tracking data only for purchase intentions.

In terms of differences, we find (and the other studies did not) a role for product quality, in that ad weight increases ad and brand awareness more for relatively high-quality brands. Further, we find that a high-priced brand tends to gain less in ad-induced purchase intent than an average-priced brand, presumably because the higher price itself communicates or serves as a quality or image cue, thus reducing the relative impact of ad weight. Finally, we find (and they did not) that ad weight effects on intentions go up with ad copy that focuses on product benefits and down with copy stressing image, humor, or emotion, at least for brands that do not already have high in-store displays or use sampling. No such result apparently emerged in the earlier studies.

In fact, the effects we found for promotional variables are complex and do not always agree with those from the IRI studies. Lodish et al. (1995) found that high trade promotion support reduced ad weight effects on sales. We found trade promotion support to be helpful in increasing ad effects on purchase intentions as long as the ad copy or strategy was new, but not if the brand was mature and of low quality (a "decliner"). And while Lodish et al. found that higher levels of consumer couponing increased ad weight effects on sales, no such effects appeared in our data. We also found results for in-store displays and sampling on our awareness and intentions variables that were complex and hard to understand. Perhaps our promotion variable results are suspect because of the limited quality and reliability of our promotional support data.

In terms of the "main effects" of advertising weight, we found the effects of advertising GRPs themselves to be highly significant (and about equal) for ad and brand awareness, but not significant for purchase intentions.

Limitations and Future Research. Our data sample is somewhat small, our intermedia aggregation of GRPs ignores qualitative differences across the media where the money is spent, and our subjectively coded moderating variables potentially contain significant measurement error. Perhaps the biggest limitation of the present study, however, is our technical inability to correct for the "lack of independence" of many of the observations. It would have been desirable to model this explicitly and to estimate the effects of advertising separately for each of the 29 separate campaigns for which data were provided. Unfortunately, most tests covered only a few (typically 4) time periods, so that after using a lagged dependent variable they usually only generated 3 or so observations. Since the models had at least 4 parameters, estimation at the campaign level was infeasible. We therefore pooled the observations across tests in our meta-analytic design. Given the number of campaigns (29), it was also not possible to reliably estimate individual test variances/effects. We therefore made the reasonable but untestable assumption that systematic differences are largely accounted for by the situational moderating variables modeled in our meta-analysis. The disadvantages of our "forced pooling" are hopefully offset by the advantages of our meta-analytic approach. However, future research must clearly try to use bigger samples, with longer test periods, to corroborate our results.

Contributions and Managerial Implications. Despite the limitations just discussed, this study should contribute significantly to our understanding of the conditions under which increased ad spending pays off. It serves to corroborate some of the key findings of the Campbell Soup, IRI, and Nielsen studies, especially the importance of boosting ad spending when the category and brand are new or growing, and when the ad strategy is new rather than old. In addition, the fact that we obtain findings using easily available tracking data that corroborate results obtained earlier using hard-to-get experimental or single-source data is itself a valuable result, suggesting that tracking data may be of greater use than earlier assumed in building models predictive of sales results. ■

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