Cooper, Lee, Masao Nakanishi. 1988. *Market Share Analysis*. Kluwer Academic Publishers, Boston, MA.

Elrod, Terry, Michael P. Keane. 1995. A factor-analytic model for representing the market structure in panel data. *J. Marketing Res.* **32**(February) 1–16.

Fader, Peter S., Bruce G. S. Hardie. 1996. Modeling consumer choice among SKUs. *J. Marketing Res.* **33**(November) 442–452.

Guadagni, Peter, John D. C. Little. 1983. A logit model of brand choice. *Marketing Sci.* **2**(1) 203–238.

Hardie, Bruce, Leonard Lodish, Peter Fader, Alistair Sutcliffe, William Kirk. 2004. Attribute based market share models: methodological development and managerial applications. Working paper 98-009, The Wharton School, University of Pennsylvania, Philadelphia, PA.

Inman, J. Jeffrey. 2001. The role of sensory-specific satiety in attribute-level variety seeking. *J. Consumer Res.* **28**(June) 105–120.

McKinsey & Company. 2004. Consumer packaged goods, executive insights. http://www.mckinsey.com/clientservice/consumerpackagedgoods/insight.asp.

Roberts, John H., Pamela D. Morrison, Charles J. Nelson. 2004. Implementing a pre-launch diffusion model: measurement and management challenges of the Telstra switching study. *Marketing Sci.* **23**(2) 186–191.

Roberts, John H., Charles J. Nelson, Pamela D. Morrison. 2005. A pre-launch diffusion model for evaluation of market defense strategies. *Marketing Sci.* **24**(1) 150–164.

Rosenbleeth, Mitch, Chris Dallas-Feeney, Stephen S. Simmerman, Tom Casey. 2002. Capturing value through customer strategy. Booz Allen Hamilton, www.boozallen.com.

Sinha, Ashish, Joonwook Park, J. Jeffrey Inman, Yantao Wang. 2005. A factor analytic choice map approach to modeling attribute-level varied behavior among SKUs. Working paper, Victoria University of Wellington, Wellington, NZ.

Sinha, Ashish, Anna Sahgal. 2002. A general unfolding model of consumer choice among SKUs. *Australian and New Zealand Marketing Acad. Conf. (ANZMAC)*, Adelaide, Australia.

Swait, Joffre, Tulin Erdem. 2002. The effects of temporal consistency of sales promotion and availability on consumer choice behavior. *J. Marketing Res.* **39**(August) 304–320.

van Heerde, Harald J., Peter S. H. Leeflang, Dick R. Wittink. 2004. Decomposing the sales promotion bump with store data. *Marketing Sci.* **23**(3) 317–334.

Practice Prize Report

Modeling the Microeffects of Television Advertising: Which Ad Works, When, Where, for How Long, and Why?

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Most past research has focused on how aggregate advertising works in field settings. However, the information most critical to managers is which ad works, in which medium or vehicle, at what time of the day, at what level of repetition, and for how long. Managers also need to know why a particular ad works in terms of the characteristics (or cues) of its creative. The proposed model addresses these issues. It provides a comprehensive method to evaluate the effect of TV advertising on sales by simultaneously separating the effects of the ad itself from that of the time, placement (channel), creative cues, repetition, age of the ad, and age of the market. It also captures ad decay by hour to avoid problems of data aggregation. No model in the literature provides such an in-depth and comprehensive analysis of advertising effectiveness. Applications of the model have saved millions of dollars in costs of media and design of creatives.

Key words: advertising response; wear-in; wear-out; carry-over effect; long-term effect; ad creative; ad cues
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Introduction

Firms spend billions of dollars each year on media advertising, yet much of this expenditure is made with limited testing of how or whether these expenditures will pay out in terms of sales and profits. Published studies on advertising's effectiveness have generally studied the aggregate effects of advertising on sales or market share. Most have focused on technical issues involved in efficiently capturing the

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unbiased effects of advertising using field data. The consensus from this research is that advertising does affect sales, though its elasticity is small and difficult to estimate (e.g., Sethuraman and Tellis 1993, Tellis 1988, Tellis and Weiss 1995).

One reason the elasticity is small could be that it reflects an average of many factors, including the medium, timing, repetition, age of the market, ad age (wear-in and wear-out), and ad creative cues (defined here as ad execution or content elements). Some of these factors might contribute to strong effects, while others might be weak or have no effect at all. Knowledge of the impact of these individual factors would greatly help managerial decision making. In particular, managers today need to know which particular ad works, in which medium or vehicle, at what time of the day for broadcast media, at what level of repetition, for how long, and in which market. Managers also need to know why a particular ad works and which aspects of its creative cues need to be changed to make it more effective. These questions are important because they reflect the way managers create and schedule advertisements, and hence they are critical to advertising creative and to media decisions. The need is all the more acute given increasing pressure on managers to show tangible performance outcomes from ad expenditures. No model or study has so far has addressed all or even most of these issues simultaneously.

The model described in this paper is designed to provide insight into all these issues simultaneously. The model was initially developed and applied in the context of a leading provider of toll-free medical referral services called Futuredontics (see Chandy et al. 2001, Tellis et al. 2000). It has since been successfully applied to a number of other contexts. The model and approach also have important research implications because they join two substantively relevant yet largely independent streams of academic research: consumer behavior and econometric modeling. The consumer behavior stream has focused on advertising creative content, testing with experiments that creative cues or what content elements of an ad achieve a better impact on consumer behavior. The econometric modeling has focused on estimating the effect of ad intensity (in terms of dollars, gross rating points (GRPs), or exposures) on sales.

The sections below outline the existing approaches to the problem in the application context and the field. We then describe our model with particular focus on its implementation, novel insights, and impact on marketing practice. Next, we highlight some illustrative outputs and analyses made possible by the model. We end with a discussion of the model's scope of application.

Existing Approaches to the Problem

In the section that follows, we provide a context for our model's impact, first describing the approach to creative, media decisions, and ad testing taken at Futuredontics, a medical referral service for which our model was initially developed. We further underscore its contribution by describing the two main approaches typically used in the advertising industry to test advertising effectiveness (split-cable single-source experiments and call tracking). We articulate the disadvantages of these approaches and illustrate how our approach avoids the disadvantages.

Approach at Futuredontics

Futuredontics operates a dentist referral service (1-800-DENTIST™) that advertises in more than 60 major markets in the United States. Their multimillion-dollar advertising budget includes more than 5,000 TV ad exposures per month. The company also runs some radio and billboard ads. Currently, Futuredontics receives more than three million calls per year to its toll-free referral service. Callers are connected to a call center in Santa Monica, California, that employs more than 80 operators. The operators collect information on the preferences of each caller and seek to match these preferences to the profiles of dentists in the company's member database. In the event of a match, the caller is connected to the office of the matching dentist. Such a connection is called a referral. The referral is free to the caller. Dentists listed in the database pay a monthly membership fee.

Our involvement with Futuredontics began in 1996. At that time, and consistent with traditional advertising practices, managers at Futuredontics used a combination of GRPs, Nielsen ratings, promotional offers from media outlets, and their own experience, intuition, and informal analyses (described later) to determine which ads to run, when, where, and how often. To minimize costs while increasing ad exposures, Futuredontics often sought "floating" spot ads, whereby TV vehicles would provide price discounts to the firm, provided they retained some discretion on exactly when the company's ads would run.

This simple approach at Futuredontics suffered from at least four problems also prevalent in the two more-sophisticated state-of-the-art approaches used in the advertising field and described below.

Approach of Split-Cable Single-Source Experiments

The split-cable single-source approach is used by IRI and Nielsen and described in a series of articles by Lodish and his colleagues (e.g., Lodish et al. 1995a, b). The approach consists of the following steps:

1. Split a panel of cable subscribers in a city so that they receive different ads.

2. Collect cumulative ad exposure and sales from households in these separate conditions.

3. Check differences in sales responses by level or type of advertising.

Notably, this approach suffers from one or more of the following limitations, which our approach avoids:

• *There is no mechanism to evaluate the creative content of the ad*. The system uses only a small set of ads. There is neither a scale nor a method by which specific elements of an ad (e.g., celebrities, arguments, music) can be included to assess which element(s) best drive sales. Moreover, the system does not evaluate how frequently one can use an ad before wear-out sets in.

• *There is no mechanism to evaluate the role of media and time of day*. The split-cable approach does not separate the effects of TV media channels or times of the day from that of the creative characteristics or repetition of the ad. For example, how much of the effect of advertising on sales is due to the program (e.g., *Friends*), its prime-time placement, creative aspects of the ad, or ad frequency? The ability to tell exactly what drives sales can help in the appropriate design, choice, placement, and scheduling of ads.

• *It is difficult to assess the carryover effects of advertising*. It is well known that advertising has carryover effects. However, it is also well known that such effects are biased upward with the use of aggregate data. Because split-cable tests involve aggregate data, the effects of advertising are potentially biased upward.

• *Analysis is limited to a few ads and test sites*. Only a few ads are tested in a few cities. The analysis is rarely conducted over the whole library of ads, population of cities, respondents, and regions.

Note that these limitations relate to the specific methods and models used to design and analyze split-cable experiments. They are not intrinsic to single-source data, so our model could also be used by firms such as IRI or Nielsen.

Approach of Call Tracking

Two common approaches to call tracking are used to evaluate responses to advertising in the toll-free advertising market:

1. Track calls during and immediately after the airing of each ad. Prior to our involvement, Futuredontics was informally using this approach.

2. Track calls from multiple 800 numbers—a different number for each vehicle—to identify which vehicle yields more calls. Many infomercials use this approach; they forgo the use of mnemonic numbers in order to be able to track calls more closely.

However, these approaches suffer from one or more of the following problems, which our model avoids:

• *There is no mechanism to evaluate the role of the creative characteristics or cues of the ad*. There is neither a scale nor a method by which various characteristics of an ad can be included in the model. As such, the creative executional elements that drive sales are unknown.

• *It is difficult to build brand equity*. A single number (especially a mnemonic number) is far superior to scattered generic numbers in its ability to enhance the future effects of advertising and to increase familiarity with the number and service.

• *It is hard to isolate all drivers of sales volume*. For example, the approach does not allow one to assess how much of the advertising effect is due to the vehicle (e.g., NBC) or to the ad itself. The ability to tell exactly what drives call volume can help spot problems quickly. Perhaps the problem lies in a weak creative, or the problem could lie in the vehicle used. Perhaps a new media plan is needed to draw new groups of consumers.

• *It prevents an accurate assessment of carryover effects*. This problem is similar to the use of simple models and aggregate data.

Again, these problems are due to the method or model of call tracking in use. They are not intrinsic to the form of the data per se.

Our Approach

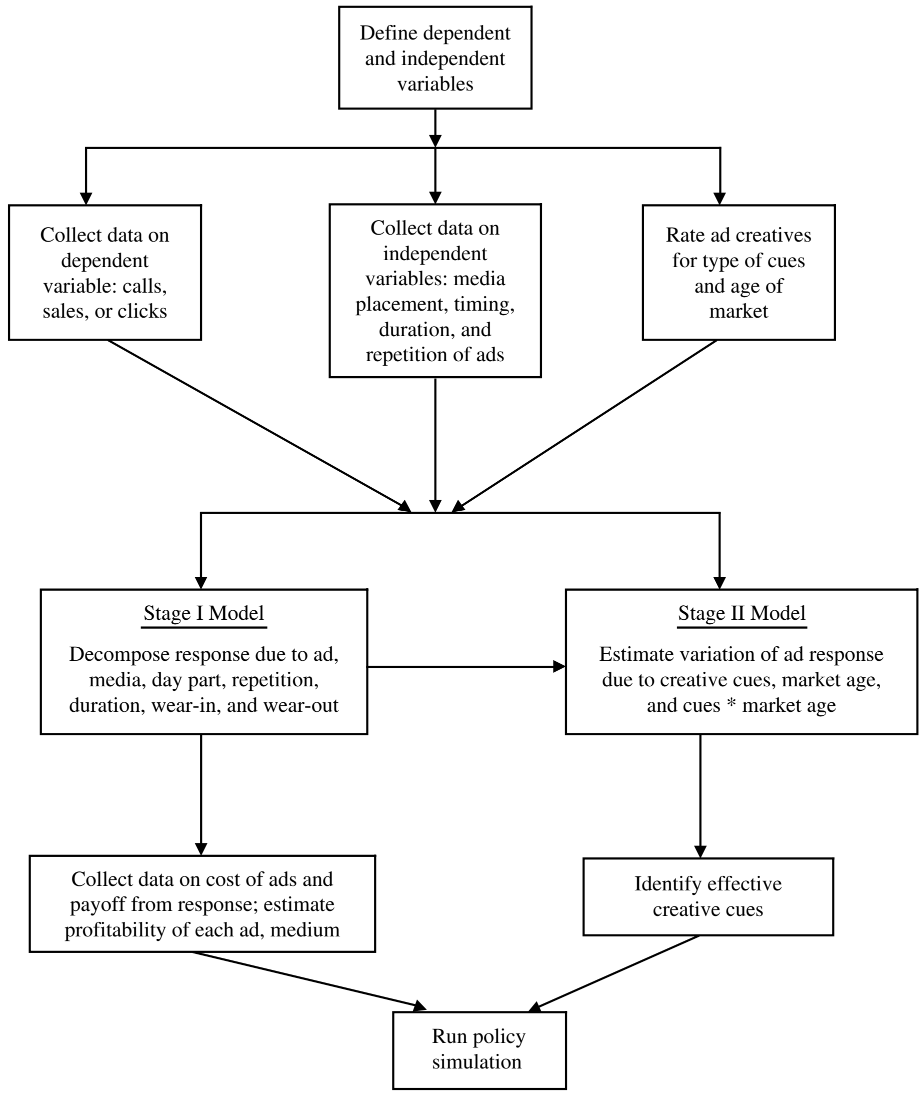
Our approach addresses each of the problems that limit the above approaches. It allows an advertiser to build brand equity around a single distinctive name. At the same time, it allows for a systematic, comprehensive, and reliable assessment of which ad works, when, where, and how often, how the advertising effect decays over time, and how repeated use of an ad wears out over time. Importantly, it can tell which creative elements in an ad work most effectively so the advertiser can develop better ads in the future. Our method is unique in this regard.

We describe our approach in four sections: Data Preparation, Model, Analysis 1, and Analysis 2. Figure 1 provides a schematic overview of the approach.

Data Preparation

Our initial task at Futuredontics involved compiling data in a manner suitable for statistical analysis. To compile the history of calls and referrals made through the toll-free number, it was necessary to first obtain the telephone logs for the number and identify the time of each call and the area codes associated with each call. The information from the telephone logs was then used to further identify the hour in which each call was made and the designated market area (DMA) from which it originated. This process resulted in a count of the number of calls and referrals made in each hour for each market.

Figure 1 Flow Diagram for Micromodeling of Ad Response



The data on the level of usage of each creative, vehicle, and media type were available from the billing invoices from each vehicle. The invoices, stored by the company in paper form, specify which ads aired on a particular vehicle during the period covered by the invoice, the time at which the ads were aired, and the cost associated with airing the ad. To compile the history of ad placements in each market, it was necessary to convert this information to electronic form. It was also necessary to match each vehicle with its DMA, so that ads on the vehicle could be linked to the referrals received from that DMA.

The above steps yielded a database that contained the number of referrals received and the specifics of the media execution of the company for each market in each hour over a relatively long period of time. This database permitted the modeling of a number of important issues on advertising effectiveness.

Model

The model uses a two-stage hierarchical design (Chandy et al. 2001). The first stage estimates the effectiveness of various ads across markets.

$$R = \alpha + \big(\mathbf{R}_{-l}\lambda + \mathbf{A}\beta_A + \mathbf{A}_M\beta_M + \mathbf{S}\beta_S + \mathbf{SH}\beta_{SH} + \mathbf{HD}\beta_{HD} + \mathbf{C}\beta_c + \big)O + \varepsilon_t, \quad (8)$$

where

$R =$ a vector of referrals by hour, $\mathbf{R}_{-l} =$ a matrix of lagged referrals by hour, $\mathbf{A} =$ a matrix of current and lagged ads by hour, $\mathbf{A}_M =$ a matrix of current and lagged morning ads by hour, $\mathbf{S} =$ a matrix of current and lagged ads in each TV station by hour, $\mathbf{H} =$ a matrix of dummy variables for time of day by hour, $\mathbf{D} =$ a matrix of dummy variables for day of week by hour, $O =$ a vector of dummies recording whether the service is open by hour, $\mathbf{C} =$ a matrix of dummy variables indicating whether or not an ad is used in each hour, $\alpha =$ constant term to be estimated, $\lambda =$ a vector of coefficients to be estimated for lagged referrals, $\beta_i =$ vectors of coefficients to be estimated, and $\varepsilon_t =$ a vector of error terms, initially assumed to be I. I. D. normal.

The second-stage analyzes the effectiveness of the ads as a function of the measured ad creative characteristics (emotion, argument, etc.).

$$\begin{aligned}\beta_{c,m} = {} & \varphi_1 \text{Argument}_c + \varphi_2(\text{Argument}_c \times \text{Age}_m) \\ & + \varphi_3 \text{Emotion}_c + \varphi_4(\text{Emotion}_c \times \text{Age}_m) \\ & + \varphi_5 800\,\text{Visible}_c + \varphi_6(800\,\text{Visible}_c \times \text{Age}_m) \\ & + \varphi_7 \text{Negative}_c + \varphi_8(\text{Negative}_c \times \text{Age}_m) \\ & + \varphi_9 \text{Positive}_c + \varphi_{10}(\text{Positive}_c \times \text{Age}_m) \\ & + \varphi_{11} \text{Expert}_c + \varphi_{12}(\text{Expert}_c \times \text{Age}_m) \\ & + \varphi_{13} \text{NonExpert}_c + \varphi_{14}(\text{NonExpert}_c \times \text{Age}_m) \\ & + \varphi_{15} \text{Age}_m + \varphi_{16}(\text{Age}_m)^2 + \boldsymbol{\Gamma}\,\textbf{Market} + v, \quad (9)\end{aligned}$$

where

$\beta_{c,m} =$ coefficients of creative c in market m from Equation (1),

Age = market age (number of weeks since the inception of service in the market),

Market = matrix of market dummies,

$\boldsymbol{\Gamma} =$ vector of market coefficients,

$v =$ vector of errors,

and other variables are as defined in Equation (4).

Equations (1) and (2) are estimated sequentially. The estimated coefficients are unbiased because the measurement error in the dependent variable in Equation (2) can be absorbed in the disturbance term of the equation and ignored (Greene 2003, p. 84). The next section summarizes two analyses that address a number of research questions of interest to advertisers (see Tellis et al. 2000, Chandy et al. 2001). We focus here on key results and impact on practice.

Analysis 1: Which Ads Work, When, Where, and for How Long?

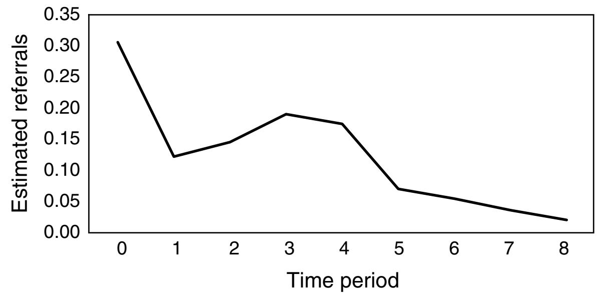
This analysis was based on the first stage of the two-stage hierarchical approach (Model 1). Its goals, results, and impact are as follows.

Goals. The goals of study 1 were to determine the following specifics of advertising effectiveness:

- Which particular ads were effective?
- When or at what times were they effective?
- Where or on which vehicle were they effective?
- For how long were they effective or how long was the time for wear-in and wear-out?

The entire analysis was at a highly disaggregate (hourly) level. We used a distributed lag model with a highly flexible carryover effect that incorporated nonlinear decay over hour of the day (Tellis et al. 2000).

Figure 2 **Nonmonotonic Ad Carryover in Sacramento**

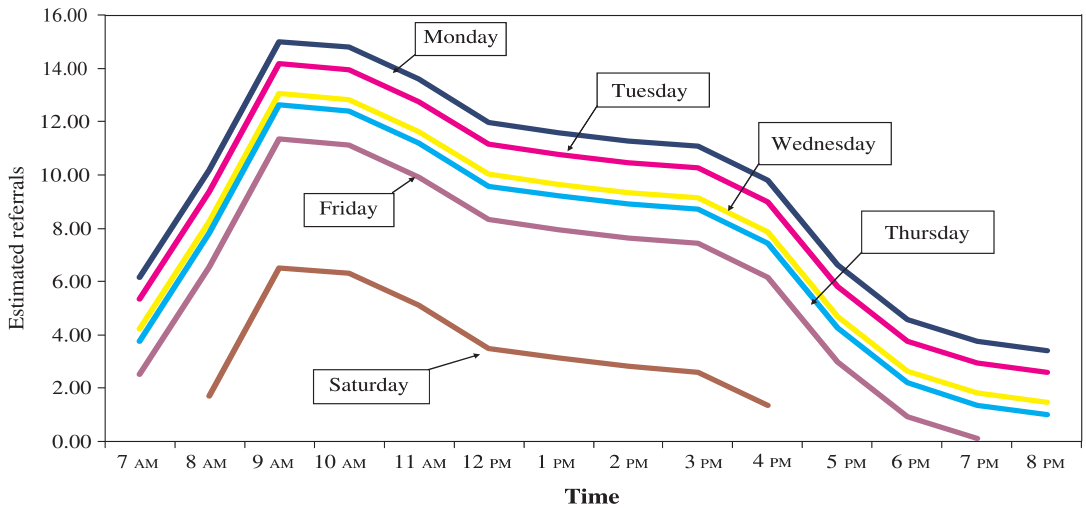


Note. Advertising carryover decays rapidly and mostly dissipates within eight hours.

Results. The estimation of the first-stage model led to the following key results. First, advertising carryover decays rapidly and mostly dissipates within eight hours (Figure 2). Additional analysis reveals that the peak of the carryover effect generally occurs in the current hour for daytime advertising but in subsequent hours for morning advertising. Thus, daytime advertising decay generally follows an exponential pattern, whereas morning advertising decay follows an inverted U-shaped pattern. Second, the effect of advertising is over and above a baseline referral, which follows distinct patterns by time of day and day of week (Figure 3). Third, when effective, new creatives are effective immediately (that is, wear-in is immediate). However, creatives also begin to wear-out rapidly. The most rapid wear-out occurs in the first few weeks of exposure. Fourth, ads vary greatly in effectiveness and profitability, with many ads being unprofitable.

Impact on Practice. Results from the study had the following impact on practice at Futuredontics. The firm used the results for baseline sales and advertising carryover to assess call center staffing and to schedule call center operators in a manner that minimized wait times. The firm also adopted an advertising schedule that focused on heavier advertising in the early part of the week, a Sunday to Tuesday schedule or a Monday to Wednesday schedule, and completely dropped advertising on Thursdays, Fridays, and Saturdays. Michael Apstein, CEO of Futuredontics at the time this research was conducted, estimates that this shift provided a savings of 30%–35% of media expenditures. Based on decay pattern results, Apstein noted, “We realized that we could go completely off air for one week out of four months.” This finding resulted in savings of more than \$1 million on media each year. Results also indicated that advertising effects differ substantially by TV channel and ad creative. Many vehicles and creatives did not contribute to an increase in referrals. The firm used this

Figure 3 Baseline Referrals in Chicago by Hour of Day



Note. Baseline referrals follow distinct patterns by time of day and day of week. The peaks in the curves indicate the hours in which customers are most likely to respond to the service. Knowledge of this pattern helps in planning advertising, and in staffing operators at call centers during different hours of the day. When extended to nonservice contexts, it could also help inventory planning.

information to reduce weight on the least effective creatives and channels. Apstein indicated that prior to the model the company developed creatives by a "go by your gut approach" coupled with expensive ad testing. "Once the research was done and the creative elements within the ad could be clearly identified, we became much more effective in the production of new creatives," said Apstein. The result was significant savings on the creative budget. Results also indicated that even when advertising was effective, it might not have been profitable. The firm used this information to increase weight on the most profitable vehicles, ads, and times of day. Apstein noted, "We were able to develop creatives that really addressed the questions of consumers. Those particular creatives really drove a significant increase in call volume to the company very rapidly once they were put on the air."

Ideally, modelers of ad competition, ad response, and optimal strategy (e.g., Banerjee and Bandopadhyay 2003, Dukes and Gal-Or 2003, Pauwels 2004, Vakratsas et al. 2004) should incorporate these more detailed aspects of advertising response into their models.

Policy Simulation. To facilitate use of the results for future planning, we developed Excel-based programs to simulate alternate advertising schedules and evaluate the results in terms of costs and benefits. The simulation enables the analyst to conveniently describe the results in each market and to suggest managerially actionable alternatives.

The simulation also helps managers plan media outlays and placements based on results from the model. Insights from these analyses can help in designing an advertising strategy that maximizes revenues, while minimizing costs.

Analysis 2: Why Ads Work

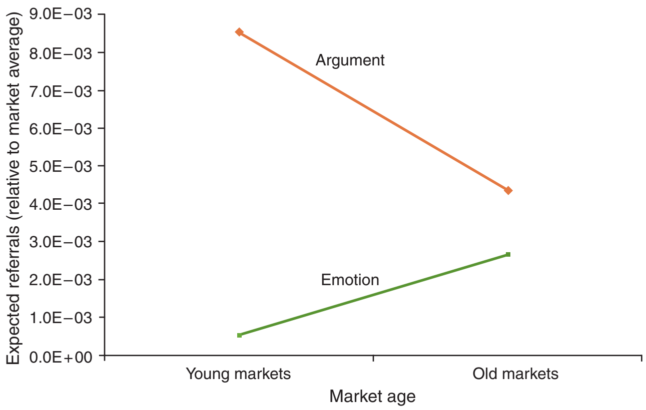
This analysis used Model 2. Its goal was to determine the creative characteristics that made specific ads effective. We describe the design, results, and impact of the study.

Design. Relying on theory in consumer information processing, we developed an instrument incorporating a rich set of creative cues, such as emotion, information, endorsers, etc. (see Chandy et al. 2001, MacInnis et al. 2002). Two trained assistants coded each ad's creative cues with this instrument. Over the years, Futuredontics developed a bank of 70 ads with varying creative content, which it scheduled without any particular pattern across 60 markets (cities) of varying ages. To determine how the effectiveness of ads varies by the age of markets and the ad's creative characteristics, we examined the interaction of age × creative cues.

Results. Ads differ substantially in effectiveness due primarily to variation in an ad's creative cues. Importantly, the effectiveness of creative cues is moderated by market age. Argument-based appeals, expert sources, and negatively framed messages are particularly effective in newer markets. In contrast, emotion-based appeals and positively framed messages are more effective in older markets. Figure 4 illustrates the results for arguments vs. emotions in young vs. old markets.

Impact on Practice. Futuredontics used these results to tailor ads that fit the age of specific markets, with different ad creative characteristics for markets of different ages. In addition, the firm designed entirely new ads with creative characteristics that

Figure 4 Effects of Argument vs. Emotion by Market Age



Note. Argument-based appeals are more effective in young markets. Emotion-based appeals are more effective in old markets. (Adapted from Chandy et al. 2001.)

better fit the age of each market. Prior to this analysis, a wild card creative had been produced quarterly just to test different creative cues. According to Michael Apstein, former CEO of Futuredontics, the elimination of the earlier approach resulted in a savings of approximately 25% of the creative budget. The firm scheduled current ads in age-relevant markets in which they would be more effective.

Cost Effectiveness Analysis

We assess cost effectiveness by conducting a cost-per-call analysis. We compare the cost of each element during the analysis period with the number of calls due to the same element during the same period.

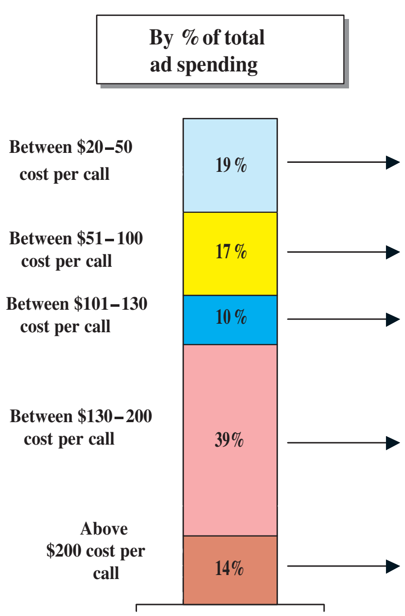
Figure 5 provides a comprehensive look at estimated costs per call and other relevant statistics for each vehicle by hour of day. (This table is illustrative and based on masked data.) The information from this analysis can be used to guide future media buying and scheduling. The rows with the lowest "estimated cost per call" are the most cost-effective. These day-parts might be worthy of increases in ad spending. On the other hand, the rows with the highest "estimated cost per call" are the least cost-effective media placements. These day-parts might be ripe for dropping, trimming, or aggressive price negotiations aimed at reducing costs.

Generalizing to Other Contexts

As a result of our model, Futuredontics was able to reduce advertising expenditures substantially while maintaining the number of calls received applied the model in all its major markets. The company has applied the model to another service category (1-800-BEAUTIFY™) with similar results. The model has also been applied successfully at 1-800-PLUMBER™, a toll-free plumber referral service. Apstein views the model as "tremendously helpful" to these contexts and as particularly critical to start-ups.

The model has also been applied by the Best Buy Corporation, the leading electronics retailer in the United States, to assess the impact of its Sunday newspaper insert advertising. Finally, the model is now the basis for an entrepreneurial start-up venture. This firm is currently in the process of further developing the model and applying it to other toll-free advertising contexts.

Figure 5 Detailed Analysis of Cost Effectiveness



Network	Time	Average cost per ad ($)	Estimated call per ad	Estimated cost per call ($)	Total usage during this period
NBC	7 AM–8 AM	106	5.0	21.2	89
WCOO	7PM–8 PM	92	3.0	30.7	95
NBC	1 PM–2 PM	172	5.0	34.4	101
NBC	9 AM–10 AM	73	1.5	48.7	85
KZYX	5 AM–6 AM	81	0.7	52.7	102
NBC	6 AM–7 AM	110	0.7	75.3	32
KXXX	7 AM–8 AM	150	0.5	81.2	50
ABC	9 AM–10 AM	370	0.3	100.5	50
ABC	10 AM–11 AM	263	0.4	110.2	41
FOX	11 AM–12 AM	233	0.5	120.5	15
NBC	12 PM–1 AM	350	0.4	128.5	22
FOX	1 PM–2 PM	547	4.2	130.3	31
NBC	2 PM–3 PM	438	3.2	137.0	31
FOX	3 PM–4 PM	183	1.3	140.5	15
ABC	3 PM–4 PM	213	1.5	141.7	20
CBS	6 PM–7 PM	580	3.2	181.2	15
CBS	11 PM–12 AM	287	1.5	191.5	20
FOX	6 PM–7 PM	1,606	8.2	195.9	20
CBS	4 AM–5 AM	118	1.7	201.2	20
NBC	6 AM–7 PM	350	0.6	222.3	11
CBS	7 PM–8 PM	600	0.4	230.5	21
CBS	4 PM–5 PM	233	1.1	250.9	51

Note. This chart provides a comprehensive look at cost-effectiveness by vehicles and day-parts.

A question we sometimes face is whether this model is applicable to other classes of products (e.g., packaged goods). Some readers point out that responses in our data are by phone, whereas consumers do not buy packaged goods by phone. We believe that our model is indeed applicable. The key issue is to track response by highly disaggregate time intervals, such as hour or minute. Whether that response is by phone, Internet, or checkout counter is immaterial. Thus, when porting our model to other contexts, all the analyst has to do is to replace the dependent variable, Referrals in the current context with order, sales, or clicks, as the case might be. The analyst will need to enhance the data with information on related characteristics (independent variables) describing their advertising, such as the time-of-day, the channel of placement, the duration of usage, a rating of the content of the ad, or age of market. Information on these latter elements is additive and separable. Thus, if information is available on some independent variables and not the others, the model can then be used for those variables on which required data should be available to advertisers.

Indeed, contrary to perception, scanner data and single-source data are even richer than the data we have used so far, because the former contain individual household information. Thus, the analyses can be done at the individual consumer level, allowing for variation in ad response by individuals. Such analyses will allow for more fine-grained segmentation.

In general, we believe the model has fairly wide applicability—all it requires is highly disaggregate data. In the current realm of abundant data collected via electronic media and stored on computers, the restriction is not data access but sound models. Thus our model is highly relevant to managers, can be readily operationalized with disaggregate data, and is generalizable across contexts.

Conclusion

We propose a comprehensive model to evaluate the effects of TV advertising on sales, which simultaneously separates the effects of the ad itself from that of the time, placement, length of usage, repetition, creative cues of the ad, and type of market in which it is shown. It also captures ad decay by hour to avoid problems of data aggregation. There is no other model in the literature that currently does such an in-depth and comprehensive analysis of advertising effectiveness.

References

Banerjee, Bibek, Subir Bandyopadhyay. 2003. Advertising competition under consumer inertia. *Marketing Sci.* **22**(1) 131–144.

Chandy, Rajesh, Gerard Tellis, Deborah MacInnis, Pattana Thaivanich. 2001. What to say when: Advertising execution in evolving markets. *J. Marketing Res.* **38**(November).

Dukes, Anthony, Esther Gal-Or. 2003. Negotiations and exclusivity contracts for advertising. *Marketing Sci.* **22**(2) 222–245.

Greene, William. 2003. *Econometric Analysis*. Prentice Hall, Upper Saddle River, NJ.

Lodish, Leonard M., Magid Abraham, Jeanne Livelsberger, Bruce Richardson, Mary Ellen Stevens. 1995a. A summary of fifty-five in-market experimental estimates of the long-term effect of TV advertising. *Marketing Sci.* **14**(3) 143–140.

Lodish, Leonard M., Magid Abraham, Stuart Kalmenson, Jeanne Livelsberger, Beth Lubetkin, Bruce Richardson, Mary Ellen Stevens. 1995b. How TV advertising works: A meta-analysis of 389 real world split cable TV advertising experiments. *J. Marketing Res.* **32**(May) 125–139.

MacInnis, Deborah J., Ambar Rao, Allen Weiss. 2002. Assessing when increased media weight of real-world advertisements helps sales. *J. Marketing Res.* **39**(November) 391–407.

Pauwels, Koen. 2004. How dynamic consumer response, competitor response, company support, and company inertia shape long-term marketing effectiveness. *Marketing Sci.* **23**(4) 596–610.

Sethuraman, Raj, Gerard J. Tellis. 1991. An analysis of the tradeoff between advertising and pricing. *J. Marketing Res.* **31**(2) 160–174.

Tellis, Gerard J. 1988. Advertising exposure, loyalty, and brand purchase: A two-stage model of choice. *J. Marketing Res.* **15**(2) 134–144.

Tellis, Gerard J., Doyle Weiss. 1995. Does TV advertising really affect sales? *J. Advertising* **24**(3) 1–12.

Tellis, Gerard, Rajesh Chandy, Pattana Thaivanich. 2000. Which ad works, when, where and how often? Testing the effects of direct TV advertising. *J. Marketing Res.* **37**(February) 32–46.

Vakratsas, Demetrios, Fred M. Feinberg, Frank M. Bass, Gurumurthy Kalyanaram. 2004. The shape of advertising response functions revisited: A model of dynamic probabilistic thresholds. *Marketing Sci.* **23**(1) 109–119.