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The authors develop a model to decompose the effects of television advertising for a toll-free referral service, at the hourly level. The model estimates which ad works, when, in which station, and for how long. Results of the analysis show that ads do stimulate direct response, but their effects dissipate very rapidly. Effectiveness and profitability vary substantially by creative, television station, and station x time of the day. The results underscore the need for managers to undertake such analyses and for researchers to use such a disaggregate approach.

Which Ad Works, When, Where, and How Often? Modeling the Effects of Direct Television Advertising

For the past four decades, modelers have tried to estimate the effects of advertising on brand sales using field data (Leone and Schultz 1980; Vakratsas and Ambler 1996). Most of these studies have focused on the many technical issues involved in efficiently capturing the unbiased effects of advertising, given the limitations of field data (Hanssens, Parsons, and Schultz 1990). Meta-analyses of these studies have shown that the effects of advertising are significantly greater than zero but vary by market and product characteristics (Assmus, Farley, and Lehmann 1984; Sethuraman and Tellis 1991). More recent studies based on single-source data have also found some significant effects of advertising (Deighton, Henderson, and Neslin 1994; Kanetkar, Weinberg, and Weiss 1992; Pedrick and Zufryden 1991; Tellis 1988; Tellis and Weiss 1995). However, the latter studies have generally found the effects of advertising to be fragile and dependent on certain conditions.

Partly because of the fragility of advertising's effects and the complexity of getting bias-free estimates, few studies have addressed the next most important issues about advertising's effects on sales: how the effects vary by creative, medium or vehicle, and time of day for broadcast advertising (e.g., Bhattacharya and Lodish 1994). In particular, no study has researched the effects of advertising by these three factors simultaneously. Ironically, managers do not need to know merely whether advertising works in some broad way. Rather, they need to know which particular advertising creative works, in which medium or vehicle, and at what time of the day, because that is the way they schedule ads. Indeed, some recent large-scale field experiments suggest that only half of ads tested actually worked (e.g., Lodish et al. 1995). Moreover, changes in medium or creative were more likely to change advertising effectiveness than were even huge increases or decreases in advertising level (e.g., Eastlack and Rao 1989). If only some ads work, and that also depends on the creative and medium, then any finding about the total effect of advertising has little practical value to marketing managers. The total is just an average of good and bad, of failures and successes, of effective and ineffective. The money is in the details: which ad, when, where, and how often.

This issue is gaining greater importance for several reasons. First, media advertising continues to draw a major proportion of the promotion budget, totaling $67 billion in 1996 (Endicott 1997). Second, because of the immediate and pronounced effects of sales promotions, advertising agencies are under increasing pressure to show the specific effects of advertising on sales. Third, the growth of electronic commerce and measurement has increased the availability of fairly precise records of advertising and sales. Fourth, despite four decades of work, few field studies answer the critical questions: Which ad works, when, where, and for how long?

This study proposes a model that can answer these questions. The model is developed in the contexts of the advertising effort and telephone responses for a direct marketer.

The goal of the model is not to obtain the most accurate and complete picture of the role of advertising. Rather, the goal is to provide managers with a useful evaluation that tells them which ads to drop and which to continue and at what times and stations to schedule them. The model is also a good starting point to address other related questions about scheduling ads for optimum response. By testing across multiple markets, the model also provides tentative generalizations about the broad aspects of advertising in terms of size, carryover, and duration effects.

This article reports on our development and test of the model. In the first section we review the theory of advertising response. In the second section we present the model. In the third section we provide the results. In the final section we discuss the implications and limitations of the results.

THE EFFECTS OF ADVERTISING

This section first describes the context of the study and then applies advertising theory to explain what types of effects we may expect from advertising in this context.

Study Context

We focus primarily on television advertising by a firm that provides a referral service for consumers seeking a medical service. The firm advertises a toll-free number that customers can call to get an appointment with a service provider. Consumers know of the service under a brand name that reflects the toll-free number that is advertised (e.g., 1-800-BUILDER™, 1-800-DOCTORS™, 1-800-LAWYERS™). They probably seek the service because they have recently moved, are unhappy with their current service provider, or have an immediate need for the service. When a customer calls the number, a representative of the firm answers the call. The representative queries the customer and then recommends a suitable service provider on the basis of location, preferences, and specific type of service needed. Typically, the representative tries to connect the customer to the service provider directly by telephone to minimize delay, miscommunication, and loss of customers. Any resulting contact between a customer and the service provider is called a *referral*. Customers do not pay a fee for the referral, but service providers, who are the firm's clients, pay a fixed monthly fee for a specific minimum number of referrals per month. The firm screens service providers before including them as clients. The firm began operations in March 1986 in the Los Angeles market with 18 service providers and a $30,000 monthly advertising budget. It currently advertises in 62 major markets in the United States, with a multimillion-dollar advertising budget that includes more than 3500 television ad exposures per month. The firm has no serious competition at present.

The key dependent variable of interest to the firm is referrals. A referral is a call by a customer for the firm's service and its successful connection to a service provider by a firm's representative. The primary marketing variable that affects referrals is advertising. There are no distribution effects, product visibility effects, or store effects. The firm does not use sales promotions such as games, premiums, coupons, and so on. The firm has received some limited publicity, but that was to sign up more providers rather than to increase referrals. The primary means of advertising is television, though in some cities the firm advertises through radio, billboards, and yellow pages. In addition to advertising, experience and word of mouth may also affect referrals.

Why and How Advertising Generates Referrals

The firm's advertising uses a variety of creatives that it airs repeatedly, primarily through various television stations at various times of the day. The theory of message repetition suggests that the effects of advertising on consumers can be broadly classified into three main effects: a current effect on behavior, a carryover effect on behavior, and a nonbehavioral effect on attitude and memory (Pechmann and Stewart 1988; Sawyer 1981; Sawyer and Ward 1976).

First, advertising has a current or instantaneous effect on referrals when consumers hear the message, are convinced of it, and respond immediately. From a practical viewpoint this study considers a response current if it occurs in the same hour as the advertising. Second, advertising has a carryover or delayed effect on behavior due to delayed response, conviction, or communication. A long tradition of econometric modeling suggests that given appropriate data and models, these two effects can be precisely estimated (Clarke 1976; Hanssens, Parsons, and Schultz 1990).

Third, ads may have some effect on attitude and memory that cannot be traced to referrals because the consumer does not have an immediate need for the service. In this case, advertising tends to build up a stock of goodwill or it may prevent forgetting of the brand name (Pechmann and Stewart 1988; Sawyer and Ward 1976). The literature indicates that this response has an inverted U-shape (Sawyer 1981). Response increases with repetition, reaches a point of saturation, and then declines. Perhaps what is less well known is the effect of repetition on learning. Studies indicate that though repetition cannot increase learning of the message beyond 100% in the short run, it does prevent forgetting in the long run (Sawyer and Ward 1976). Because the service is not one that consumers normally think about or one that consumers can access at a retail store, customers' accurate recall of the number is an important goal of the firm's advertising strategy.

Thus, even if its advertising does not lead to immediate referrals in the short run, it can build up a base for the future. It increases familiarity with the brand name, which enhances the effect of future advertising when the consumer has need for the service. It increases rehearsal and prevents forgetting of the brand name, which thus increases the chance that consumers will use the service if they need it in the future. These effects contribute to the equity in the brand name. Brand equity may also be due to the good service consumers have experienced with the firm in the past, which leads to reuse or positive word of mouth.

The firm has records of referrals and advertising by creative, medium, vehicle, and hour in each market in which it operates. Given such disaggregate data, the history of modeling advertising response indicates that we can fairly accurately capture the effect of advertising on referrals (Assmus, Farley, and Lehmann 1984; Sethuraman and Tellis 1991). The value of the model and analysis for the manager is that it can answer the following questions:

•Given the equity that has been built up in a market, through either previous advertising or the good services of the firm, how does current advertising affect referrals? In particular, (1) How does placement of ads on various television stations affect referrals? (2) How do various creatives affect referrals? (3) How does advertising at various time periods affect referrals? and (4) How do age and repetition of these creatives over time affect referrals?

•If current advertising increases referrals, does the benefit from the increase cover the cost of that particular advertising?

The contribution of our model in identifying the role of advertising is conservative. It is capable of identifying the four aspects of the current and delayed effects of advertising on referrals. However, the model is unable to estimate directly the role of advertising, if any, on brand equity. This limitation is true of most econometric models. Note, however, that because of this limitation, testing whether advertising works through this model increases the probability of a type II error but decreases the probability of a type I error. We next describe a model that tries to answer the questions posed previously.

DEVELOPING THE ADVERTISING RESPONSE MODEL

This section specifies the advertising response, describes the control variables, presents informal hypotheses, and describes the method of the study.

Specifying Advertising Response

Traditionally, sales response models of advertising have modeled advertising response at the quarterly, monthly, or weekly level (Assmus, Farley, and Lehmann 1984; Sethuraman and Tellis 1991). However, we model advertising response at the hourly level for three reasons. First, the firm uses multiple ads and stations in a day, so, to analyze ad effectiveness accurately by creative, station, and time of day, the data must not be more aggregate than hourly. Second, disaggregate data always ensure more efficient estimates and generally provide less biased estimates (Judge et al. 1985). Third, in the presence of dynamic advertising effects, disaggregate data ensure a more faithful recovery of the underlying dynamics (Tiao and Wei 1976).

The primary explanatory variable in the model is television advertising, which we expect to have current and carryover effects. In such a situation, the effect of advertising can be captured by a general distributed lag model as follows:

$$(1) \quad R_t = \alpha + \gamma_1 R_{t-1} + \gamma_2 R_{t-2} + \gamma_3 R_{t-3} + \dots + \beta_0 A_t + \beta_1 A_{t-1} + \beta_2 A_{t-2} + \dots + \varepsilon_t,$$

where

$$t = \text{an index for time period,}$$
$$R = \text{referrals per hour,}$$
$$\alpha, \beta, \gamma = \text{coefficients to be estimated,}$$
$$A = \text{ads per hour, and}$$
$$\varepsilon = \text{errors.}$$

Equation 1 has several advantages. First, the presence of both moving-average (MA) and autoregressive (AR) components reduces the need for infinite or numerous lags on A or R. The reason is that, in certain conditions, an infinite-order MA can be captured by a first-order AR term, whereas an infinite-order AR process can be captured by a first-order MA term. Second, various combinations of even a few terms

of γ and β enable the advertising decay to take on a rich variety of shapes. The values of γ primarily influence the rate at which the carryover effect peaks and decays, while the values of β influence the number and height of the peaks (for a slightly different interpretation, see Clarke 1976). Third, the relative values of γ and β enable us to differentiate between carryover and purchase reinforcement effects of various orders, if that is of importance (e.g., see Givon and Horsky 1990).

Advertising at different times during the day may have different decay structures. In particular, because consumers are often rushed during the morning, they may take longer to respond to morning ads relative to ads at other times of the day. To test this difference, we include a variable for morning advertising and its corresponding decay. As stated previously, the data also record the nature of advertising by creative and television station. So we include variables for the number of times each creative and station were used in each hour,[1] with their corresponding lags.

The advertiser uses various stations primarily to appeal to specific segments. For a particular station, the target segment may change by hour of the day because of the availability of consumers. So we test for another interaction term, station x hour of the day. Besides television, other advertising media are infrequent. In a few markets, the firm uses radio advertising. We test for the effects of radio ads in the same way as we do for television ads.

Specifying Control Variables

The referral service is not open during part of each weekend and at night. Therefore, the dependent variable is truncated, requiring the use of Tobit models (Tellis 1988; Winer 1983). Fortunately, we know the hours when the service is open. Properly including that variable in the model can account fully for the truncation bias and avoid the necessity of complex models (Amemiya 1985; Judge et al. 1985). Thus we interact this variable with every explanatory variable in the model, because no variable can have any effect on referrals unless the service is open.

Medical calls, as indeed calls for most services, vary over days of the week and are highest just after the weekend. Also, we expect calls to vary by hour of the day as consumers' free time varies. So we include dummy variables for each hour of each day that the service is open. In the interest of parsimony, we do not control for the effects of seasons, special holidays, and probable breakdowns in the answering service. Although these effects may not be zero, preliminary analyses indicated that they were not substantial enough to merit incorporation at this early stage of analysis.

Specifying Full Model

On the basis of the previous discussion, we test the following model:

$$(2) \quad R = \alpha + (R_{-l}\lambda + A\beta_1 + A_M\beta_2 + C\beta_3 + S\beta_4 + SH\beta_5 + HD\beta_6)O + \varepsilon_t,$$

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[1]Note that the specification of these three sets of variables may also be considered a second-order interaction between advertising and three factors: time in hours, television stations, and type of creative. We find that not stating them as interactions makes the exposition of the model simpler.

where

R = a vector of referrals by hour;

R_{-l} = a matrix of lagged referrals by hour;

A = a matrix of current and lagged ads by hour;

A_M = a matrix of current and lagged morning ads by hour;

C = a matrix of current and lagged ads for each creative by hour;

S = a matrix of current and lagged ads in each television station by hour;

H = a matrix of dummy variables for time of day by hour;

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;

α = constant term to be estimated;

λ = a vector of coefficients to be estimated for lagged referrals;

β_i = vectors of coefficients to be estimated, indexed by i going from 1 to 6; and

ε_t = a vector of error terms, initially assumed to be i.i.d. normal.

Note that bold roman letters refer to matrices that represent sets of related variables measured by hour. Advertising is measured as the number of ads appearing in an hour.

Hypotheses

Considering the theory and the model specified, we list some informal expectations about the model's coefficients. Confirmation of these expectations would partly validate the model and contribute toward advertising theory.

Given that advertising is the sole means of marketing, we expect advertising to have a clear, positive effect on referrals. This expectation is not trivial, because most studies find the effect of advertising to be small (e.g., Assmus, Farley, and Lehmann 1984) or even insignificant, especially with disaggregate data (Kanetkar, Weinberg, and Weiss 1992; Tellis 1988).

Economists using Koyck's (1954) model and aggregate data estimated that the effects of advertising last for years. However, Clark (1976) showed that those estimates were biased upward because of aggregate data. He estimated that carryover effects of advertising should last from three to nine months. Moreover, behavioral research indicates that response to advertising is strongest in the short run (Sawyer and Ward 1976). Because we use highly disaggregate data and the purpose of each ad is to remind consumers of a toll-free number, we expect the carryover effect of advertising to be short.

Customers who watch an ad in the morning may choose to wait until the rush to prepare for work, school, and so forth is over before they call the service. Customers who watch the ad during the day may be less pressed for time and may call soon after the ad is aired. Therefore, we expect the morning ads to have a longer decay or a later peak in decay relative to daytime ads.

The firm advertises at a variety of times and on a variety of stations because it is unsure which media strategy is the best. Because ads on various stations and at various times of day appeal to different segments, we expect differences in the effectiveness of various stations and stations x time of day. The firm also uses a variety of creatives, because it is unsure which creatives are effective. Because of the vast differences in the firm's creatives, we expect differences in the effectiveness in generating referrals.

Medical calls tend to be higher after a holiday or weekend because of pent-up demand or because consumers are more sensitive to pain when work begins. Conversely, calls tend to decrease toward the end of the week as consumers get ready to enjoy the weekend. We therefore expect referrals to decline as the week progresses. We also expect referrals to peak around midday, when working consumers have more spare time to call.

Through ten years of experience with advertising and subsequent referrals, the firm has developed an implicit value of advertising in general and of its referrals to clients. The firm charges clients a fixed sum for a target minimum of 15 referrals per month. This figure enables us to calculate the approximate dollar value of each referral. Prior research indicates that firms tend to overadvertise or that much advertising is unprofitable (Aaker and Carman 1982; Lodish et al. 1995). Thus we expect the coefficients of advertising to represent a level of referrals that are, on average, marginally to substantially unprofitable.

Method

Assuming the error terms to be i.i.d. normal, we can estimate Equations 1 and 2 by least squares regression. This method is widely available and is easily estimated and interpreted. However, regression requires a proper specification of all independent variables with their associated lags, a specification of all trend, seasonal, and cyclical patterns. Moreover, regression also requires i.i.d.-normally distributed error terms or knowledge of any deviations from normality to make appropriate adjustments. A priori, researchers can never be sure of having this knowledge. They must use empirical methods to identify the appropriate lag specification and error structure.

Transfer function analysis (Box and Jenkins 1976) provides a rigorous procedure for estimating the appropriate lag and error structure. In particular, the method captures

- all trend, seasonal, and cyclical patterns in all the variables (temporal patterns),
- how the effect of independent variables transfers to a dependent variable over time (lag structure), and
- any residual AR or MA components in the series unrelated to the transfer function (error patterns).

As a result, the errors are truly white noise. Following the work of Box and Jenkins (1976), Equation 1 can be expressed as

$$(3) \qquad R_t = \alpha + v(B)A_t + N_t,$$

where R_t and A_t are stationary series of referrals and advertising, B is the backshift operator, and $v(B)$ is the transfer function of advertising on referrals. $v(B)$ is expressed as a function of two polynomials of lower order $Cw(B)B^b/\delta(B)$ (where b is the number of periods, or dead time, before advertising affects sales), and N_t is defined as $[\theta(B)/\phi(B)](1 - B)^d a_t$. $\theta(B)$, $\phi(B)$, and d are MA, AR, and difference operators, respectively, and a_t is zero-mean and normally distributed white noise.

RESULTS

We tested the models on data from five markets of differing size and age (see Table 1). The data are at the hourly level. Newer markets generally had less available data. Table 1 also gives the number of hours of data used for the analysis. Hourly data provide a rich description of the phenomenon through a large number of observations and greatly mitigate problems of collinearity (Mason and Perreault 1991). We present the results in three parts: model selection, analyses of advertising effects, and additional analyses on creatives.

Model Selection

Although it is rigorous and comprehensive, transfer function analysis is very tedious, especially in the presence of many independent variables, as in Equation 2 (e.g., Chatfield 1988; Fildes and Makridakis 1995). Moreover, the estimation frequently fails to converge when researchers deal with a large number of observations or variables. We therefore first estimate the relatively simple Equation 1 by both regression and transfer function analysis.[2] If the results

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[2]Note that the transfer function approach removes any trends (e.g., hourly, daily, weekly) by differencing the dependent and independent variables. To facilitate comparison between the two approaches, we account for hourly and daily effects in the regression model by adding dummy variables for hour x day to the basic model in Equation 1.

are similar, we estimate Equation 2 by the simpler regression. Otherwise we estimate Equation 2 by transfer function analysis. We present the discussion on model selection in three sections: temporal patterns, lag structure, and predictive ability.

Temporal patterns. An analysis of autocorrelations and partial autocorrelations for the advertising series reveals the presence of patterns at the hourly and weekly levels in each market. To achieve stationarity in the transfer function analysis, we differenced the referral and advertising series at the hourly and weekly levels. To account for temporal patterns in the regression analysis, we included appropriate dummy variables for day of the week and hour of the day when the service is open.

Lag specification. To identify the proper transfer function model, we first calculated the cross-correlation function that described the relationship between hourly referrals and advertising. The cross-correlation function indicates that the effect of advertising on referrals begins within the same hour in all markets; that is, the dead time, b, equals zero.[3] However, the cross-correlation functions

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[3]Details of the transfer function analysis are available from the authors on request.

Table 1
MODEL ESTIMATES FOR EACH MARKET

	Market				
	Sacramento	*Chicago*	*Miami*	*Minneapolis–St. Paul*	*Washington, DC*
Market started	June 1988	February 1991	August 1995	June 1996	January 1997
Sample size	19,632	2784	10,776	7848	4152
(Period studied)	(1/95–3/97)	(1/97–4/97)	(12/95–2/97)	(6/96–4/97)	(1/97–6/97)
Number of independent variables	395	235	291	317	300
Independent Variable*	Effects on Dependent Variable: Referrals (Coefficients of Equation 2 with Absolute t in parentheses)				
$Ref_{t-1} \times Open$	.12 (16.9)	.05 (2.6)	.08 (8.7)	.07 (6.1)	.07 (4.9)
$Ref_{t-2} \times Open$	.11 (15.1)	.05 (2.8)	.07 (7.4)	.01 (1.3)	.09 (5.7)
$Ref_{t-3} \times Open$	.07 (9.5)	.07 (3.5)	.05 (5.4)	.03 (2.7)	.03 (1.7)
$A_{t0} \times Open$	.38 (11.7)	.85 (5.3)	.46 (6.7)	.52 (13.5)	.60 (7.0)
$A_{t-1} \times Open$	.09 (3.4)	−.04 (.3)	.05 (1.0)	.04 (1.1)	.59 (7.0)
$A_{t-2} \times Open$	.01 (.5)	−.09 (.7)	.30 (4.4)	−.23 (6.2)	.10 (1.1)
$A_{t-3} \times Open$	−.06 (2.1)	.26 (2.0)	.13 (3.3)	.11 (3.1)	−.15 (1.7)
$A_{t-4} \times Open$	.21 (6.1)	.24 (2.0)	.16 (3.8)	.01 (.4)	.12 (1.5)
Constant	.02 (1.3)	.01 (.1)	.01 (.8)	.00 (.5)	.00 (.1)
R^2	.76	.88	.55	.48	.80
Durbin–Watson	2.00	2.00	1.98	1.99	2.02

*For ease of exposition, the coefficients for morning advertising, station, creative, hour, and day are not included in this table.

do not unambiguously indicate which lag specification was most appropriate. Models based on differing lag specifications also did not differ substantially in goodness of fit and predictive ability. We used two well-established criteria, the Akaike information criterion (AIC) and Schwarz's Bayesian criterion (SBC), to determine goodness of fit (Enders 1995; Harvey 1993). All AIC and SBC values in each market are similar to each other. The SBC indicates no lag specification that is uniformly superior across all markets. The one-week forecast errors are virtually identical across transfer function analysis lag specifications. However, the AIC indicates that a model with three lags on the dependent variable and four lags on advertising is marginally superior.

For the regression analysis, we tested several alternative lag specifications of Equation 1 to determine which was most appropriate. For the latter tests, we used the t-test of significance of the coefficient of a particular lag of advertising or referrals plus the F-test of higher explained variation by adding more lag terms. Results from the regression analysis tend to support a model with three lags on the dependent variable and four lags on advertising. This model explains a significantly higher proportion of the variance in the data relative to models with fewer lags. Additional lags did not substantially increase the explained variance. On the basis of all these tests, we decided to proceed with a model with three lags on the dependent variable and four lags on advertising.

Predictive ability. To determine the validity of regression relative to transfer function analysis, we examined the results of estimating Equation 1 through regression and transfer function using the lag structure described previously. The estimate of the total effect of advertising and its decay over time were quite similar between the two approaches. In the interests of parsimony, we subsequently present detailed results on the decay curves by one approach only.

We next estimated one-week forecasts of a holdout period for the transfer function and regression models for each market. When measured by root mean square error, or mean absolute deviation, the regression model provides comparable or slightly superior forecasts than does transfer function analysis. These findings complement results from prior research by Fildes and Makridakis (1995) and Makridakis and Hibon (1997). The reasons may be that the model estimated by regression specifies all key effects of advertising and time. Thus the error structure of the model is close to white noise. (We elaborate on this point in the Diagnostic Checks section of the article.)

Overall, the findings indicate that the results from the regression analysis are similar to those from transfer function analysis. However, transfer function analysis is tedious and time consuming. We had difficulty getting Equation 1 (with only one independent variable but thousands of observations) to converge. It would be extremely difficult, if not impossible, to estimate Equation 2 properly through transfer function analysis, because it includes scores of variables. By contrast, regression analysis is relatively easy to execute and provides explicit estimates of the effects of the hour of the day and day of the week. As we explain subsequently, these coefficients are of great interest to managers seeking to understand temporal patterns in sales. Therefore, we estimated Equation 2 using only regression analysis.

Results on Advertising Effects

Table 1 presents the estimated coefficients of the key variables from the regression analysis of the full model in Equation 2. (For ease of presentation, we do not include main and interactive effects of morning advertising, hour of day, day of week, station, and creative in this table. We present and discuss them subsequently.)

Advertising decay. As hypothesized, the coefficients of advertising are generally higher in the larger markets, thus providing face validity for the differences across markets. The cumulative or total effects of advertising (TA) can be calculated by dividing the sum of ad coefficients by 1 minus the sum of lag-referral coefficients; thus:[4]

$$(4) \qquad TA = \Sigma_{\ell = 0 \text{ to } n} \, \beta_\ell \, / (1 - \Sigma_{j = 1 \text{ to } p} \, \lambda_\ell),$$

where ℓ is an index for the time lag, and n and p represent the duration of nonzero lags of advertising and referrals, respectively. To capture the advertising decay, we need the partial advertising effect at each time period. We could not find any formula in the literature for this purpose, so we computed the partial effect of advertising, $TA_{t - \ell}$, for ℓ lags after any time period t, using the following formula:

$$(5) \qquad TA_{t - \ell} = \beta_\ell A_{t - \ell} + \Sigma_{j = 0 \text{ to } \ell} \, \lambda_j TA_{t - \ell + j},$$

where j is an index for the nonzero lags of the dependent variable $\lambda_0 = 0$, and the other terms are as defined previously. The first term on the right-hand side represents the effect of advertising that is directly effective in the ℓ lag after time period t. The second term captures the subtotal of the effect of advertising, TA, at a more recent lag, $\ell + j$, multiplied by the matching jth λ by which this effect decays to the current period.

Figure 1 plots the lag structure of daytime advertising (excluding the morning effect). Figure 2 plots the lag structure of morning advertising in each of the markets. From the figures, note that

•Advertising has a carryover effect, most of which occurs within 8 hours.
•The peak of the carryover effect generally occurs in the current hour for daytime advertising. The peak of the carryover effect generally does not occur in the current hour for morning advertising.
•The daytime peak varies from a low of .37 referrals per hour to a high of 1.59. The morning peak varies from a low of .16 referrals per hour to a high of .53.
•The daytime advertising decay generally follows an exponential decay pattern, whereas the morning advertising follows an inverted U-shaped pattern. However, these patterns are most distinct in the more mature markets, Sacramento and Chicago.

These results suggest that, as hypothesized, all consumers do not respond instantaneously to an ad. They respond over some time period, beginning with the hour of exposure. This delayed response is particularly pronounced during the morning hours, when consumers may be busy with other, more pressing activities.

Although we expected the carryover effect to be fairly short on the basis of prior theory and empirical work, we were surprised to see that much of the effect dissipated within eight hours after exposure. Though surprising, these

[4]We thank an anonymous reviewer for suggesting this equation.

Figure 1
DAYTIME ADVERTISING DECAY IN EACH MARKET
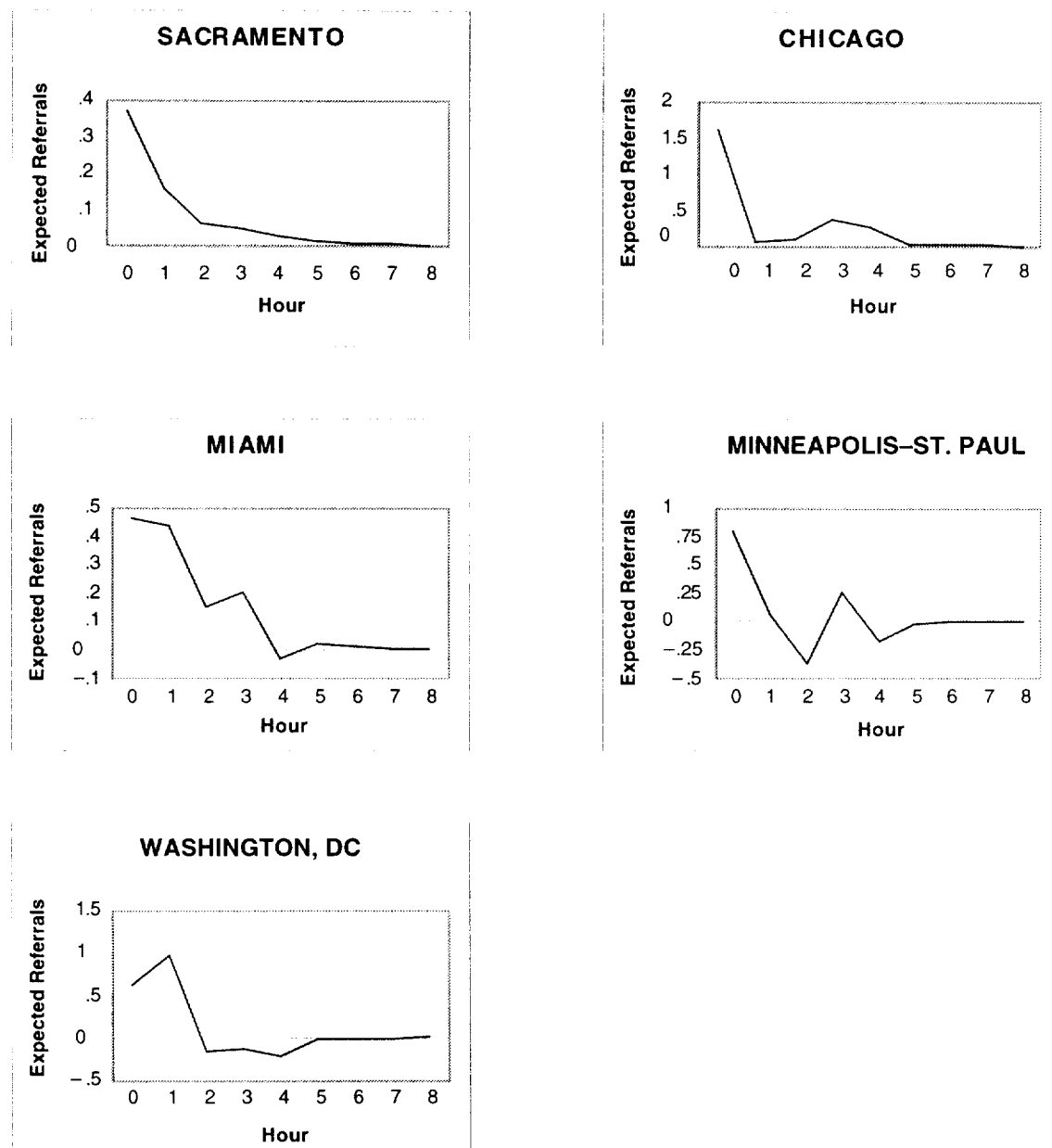
results are consistent with Clarke's finding that prior studies grossly exaggerate the duration of advertising's effect (also see Russell 1988). Moreover, for advertising that primarily communicates a toll-free number, a duration effect of eight hours seems reasonable. Indeed, management found these results quite plausible. The surprisingly short duration of effects may, however, be unique to the direct response context of this study.

Station and creative effects. Advertising effectiveness varies by station (see Tables 3 and 4). We found that a few stations had much higher or much lower effectiveness than the majority, which had average effectiveness. So, for parsimony in estimating the model and communicating findings, we included in the model only the stations with significantly

higher or lower effectiveness than average. Thus the cumulative effects of the included stations must be interpreted with reference to the excluded average stations. Table 2 indicates that the American Broadcasting Company (ABC) is the most effective network in three of the five markets. Beyond this, the effectiveness of the networks varies substantially across markets. For example, the generally weak WB network is the second most effective network in Chicago and Miami. Table 3 presents the effects of station x time after controlling for the other effects in Equation 2. The differences in the effects of station x time are larger and more frequent than are those of station alone. Note that the effectiveness varies from a high of 6.8 in Washington, DC, to a low of –8.6 in Chicago. This information can be useful for

Figure 2
MORNING ADVERTISING DECAY IN EACH MARKET
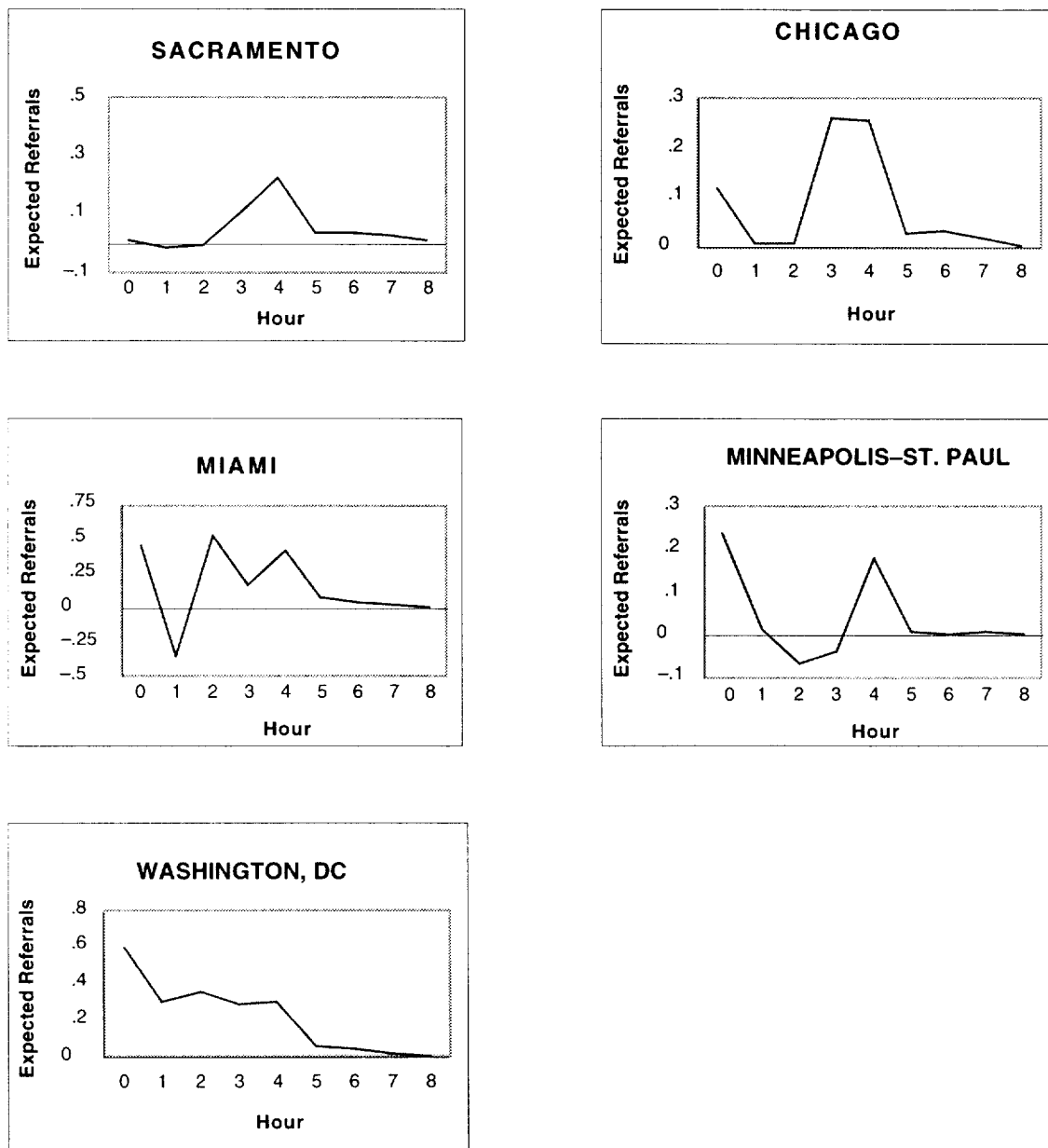
management. The stations with positive coefficients represent media placements that the firm should explore and support, while those with negative coefficients represent placements that the firm should examine and drop. This information provides managers with clear guidelines as to which particular time slots are the most productive for media buys.

Creatives also differ substantially in effectiveness. Following the same rule for standardization as for stations, Table 4 presents a summary of the effects of creatives with the strongest or weakest effectiveness relative to the creatives with average effectiveness. Management found these results to be the most interesting and informative. Here

again, positive values represent creatives that need to be scheduled more, while negative ones represent those that need to be rested or retired.

Baseline effects. The coefficients of the temporal variables, time of day and day of week, give the estimated baseline referrals after controlling for the short-term effects of advertising. The results for the average coefficient for each hour of the day are provided in Figure 3. The curves indicate that, as hypothesized, baseline referrals during the day tend to follow a bell-shaped curve. However, the curves are not symmetrical, and the peak occurs in the early morning to midmorning rather than after noon. If the timing of calls is driven primarily by time availability, the results imply that

Table 2

MAIN EFFECTS OF STATION IN EACH MARKET

	Sacramento		Chicago		Miami		Minneapolis –St. Paul		Washington, DC	
Network		Cumulative Effect	Network	Cumulative Effect	Network	Cumulative Effect	Network	Cumulative Effect	Network	Cumulative Effect
NBC	.1		ABC	2.1	ABC	1.2	ABC	.2	CBS	.4
CBS	.0		WB	1.8	WB	.5	CBS	.0	ABC	.3
FOX	.0		FOX	.0	CBS	-.1	NBC	.0	NBC	.0
ABC	-.1		UPN	.0	NBC	-.3	FOX	-.7	FOX	.0
WB	-.4		CBS	.0	UPN	-.7	UPN	-.4	UPN	.0
UPN	-.9		NBC	.0	FOX	-1.0	—	—	WB	-.6
—	—		Local	-14.1	—	—	—	—	—	—

Table 3

SUMMARY EFFECTS OF STATION X TIME IN EACH MARKET

	Market				
	Sacramento	Chicago	Miami	Minneapolis–St. Paul	Washington, DC
Number used	72	50	38	46	43
Number positive	7	6	3	7	10
Cumulative effect of most effective station x time	2.7	4.3	1.7	1.4	6.8
Number negative	9	6	5	6	1
Cumulative effect of least effective station x time	-.9	-8.6	-1.9	-1.0	-3.3

Notes: All effects listed in this table are computed relative to an abstract average station x time in the particular market. Thus a cumulative effect of 2.7 referrals indicates that each ad on this station and time resulted in 2.7 more referrals than an ad would get on the average station and time in this market.

Table 4

SUMMARY EFFECTS OF CREATIVES IN EACH MARKET

	Market				
	Sacramento	Chicago	Miami	Minneapolis–St. Paul	Washington, DC
Number of creatives used	34	8	24	19	10
Number positive	16	1	8	13	3
Cumulative effect of most effective creative	7.0	2.2	4.7	1.5	.4
Number negative	12	3	14	5	6
Cumulative effect of least effective creative	-1.8	-1.5	-3.5	-1.6	-3.2

Notes: All effects listed in this table are calculated relative to an abstract average creative in a particular market. Thus a cumulative effect of -3.5 referrals indicates that this creative resulted in 3.5 fewer referrals than the average creative on the market.

consumers have more free time in the midmorning than at midday during the lunch break. Figure 4 presents the average coefficients for each day of the week. Note that in each market, the number of calls is highest on Mondays and declines with each day of the week. The pattern confirms our hypothesis that consumers attend to medical issues more intensely at the start of the week than at the end, for reasons given previously.

Thus, with a few exceptions, most coefficients are in the expected direction. The basic model shows a great deal of similarity across markets. The R^2 is high especially in the older cities that have had more time to develop mature patterns. All these results lend support to the model.

Diagnostic Checks. Tests of autocorrelation, collinearity, and heteroskedasticity reveal no serious violations of the classic regression assumptions. The Durbin–Watson statistic is close to 2 in each market, which indicates that the model does not suffer from first-order autocorrelation. All values of the variance inflation factor are less than 10, and all condition index values are less than 30. Thus collinearity is not a serious problem (Belsley, Kuh, and Welsch 1980; Greene 1997). Finally, a visual inspection of the plots of residuals versus predicted values of the dependent variable indicates that the error variances are generally constant across increasing values of the criterion variable (e.g., Bowerman and O'Connell 1990).

Effects of Creatives and Market Differences on Ad Response

We carried out two additional analyses: one of differences in effectiveness across creatives and one of differences of ad effectiveness across markets.

Effective frequency of creatives. How long should a creative be run? What characteristics of scheduling lead cre-

Figure 3
BASELINE REFERRALS IN EACH MARKET BY HOUR OF DAY
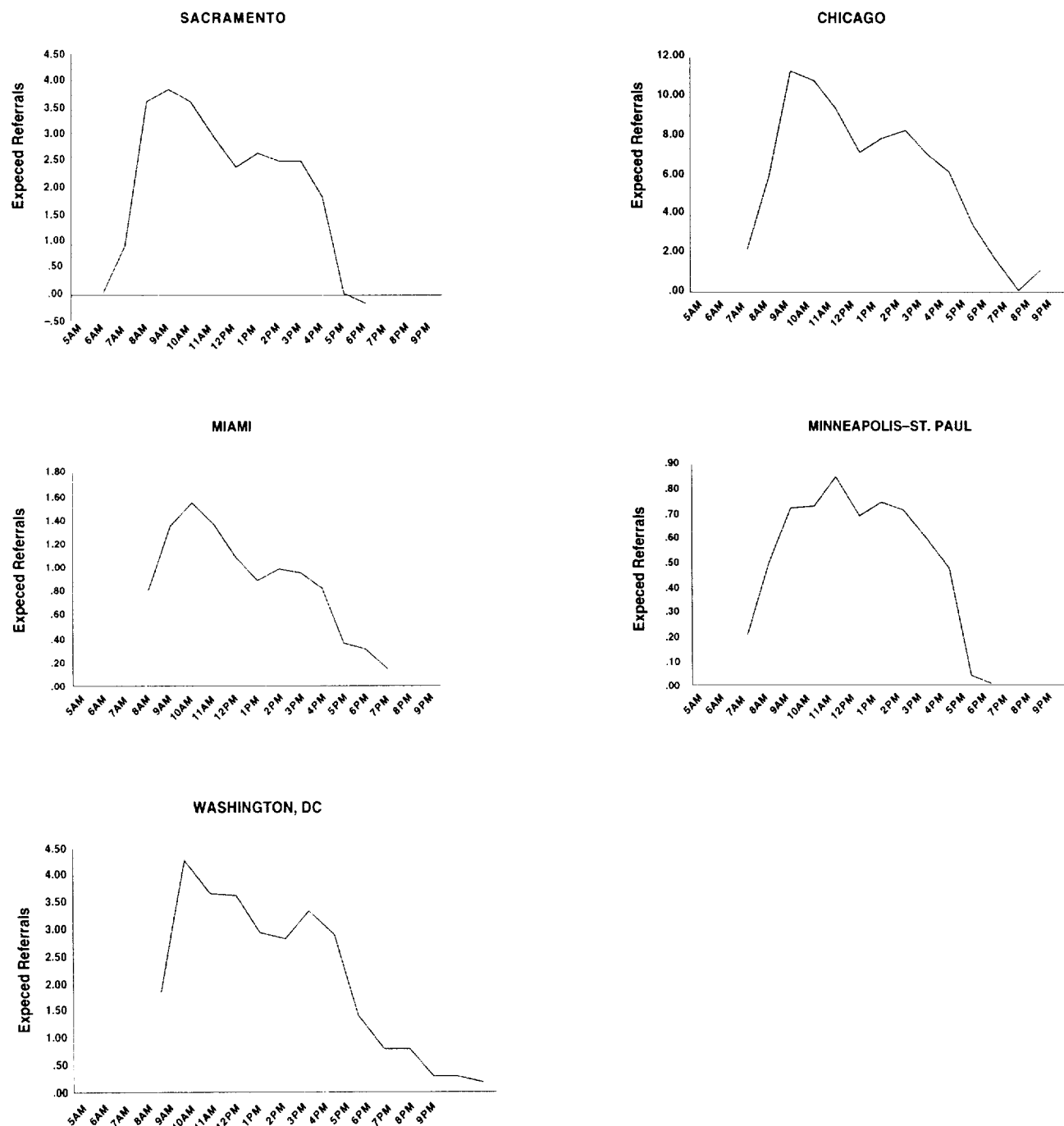
atives to be differentially effective? These questions have been addressed in the literature under the headings of "effective frequency" or "wearin and wearout." However, the estimates of our model with the current database provide a unique opportunity to address these issues with a variety of creatives in a field setting. To answer these questions, we analyzed the coefficients of creatives by age of the creatives and the frequency or intensity of use.

Creatives varied substantially by age, because the firm rarely retired ads. It repeatedly used favorite ads even if they were old. However, older creatives were likely to be less effective as consumers grew used to them and the ads' novelty wore off, so we hypothesized that older creatives may be less effective than more recent creatives. We measured age as the number of days since the ad was first created or the number of days since the ad was first shown in the market,

whichever came later. We expected effectiveness to decline exponentially with age.

Extensive research indicates that creatives initially wear in and ultimately wear out with use (Pechmann and Stewart 1988). Thus the expected curve of response is an inverted U-shape with usage. The curve occurs because of a two-factor theory of advertising response (Sawyer 1981). A new stimulus initially arouses tension in an audience. As exposure increases, tension decreases, which leads to increases in lik-

ing. At this early stage, tedium (or tiredness) with the stimulus barely increases, so net response increases with repetition. However, as repetition increases further, tedium increases rapidly with little further increase in liking. As a result, net response begins to decrease. We measured repetition by the mean usage of a creative in a station per week of flights in use. This measure is the most meaningful for managers, because it tells them how frequently to schedule a creative in a flight.

Figure 4
BASELINE REFERRALS IN EACH MARKET BY DAY-OF-WEEK
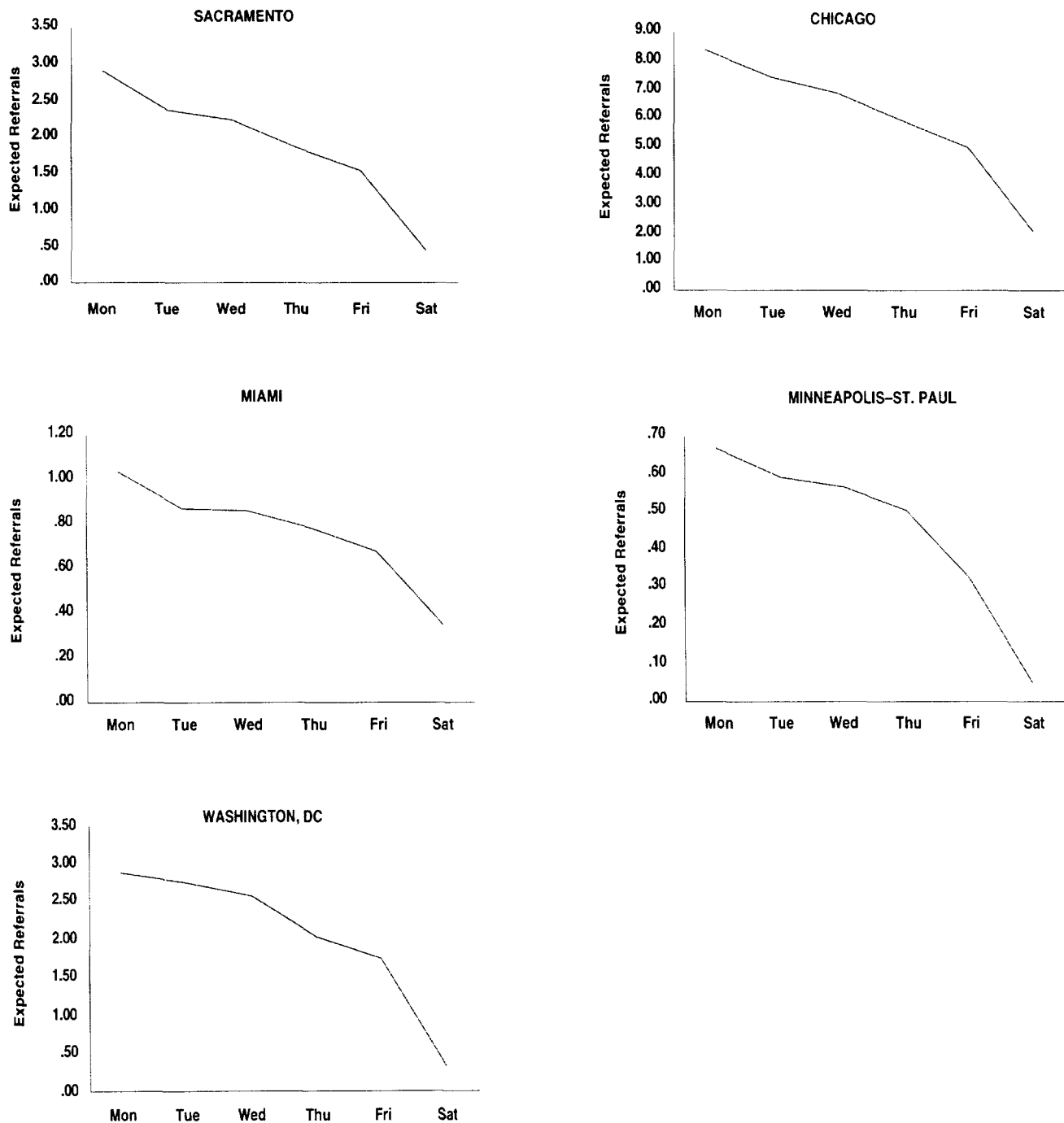
We tested these two hypotheses by regressing the cumulative effect of each creative on age and usage of the creatives. To control for market-specific effects, we also included dummy variables for four of the five markets. To capture the hypothesized nonlinearity, we used the logarithm of age of the creative (in days) and the natural and squared values of creative usage per station per week in flight.[5] We tested these effects by estimating the following equation:

$$(6) \quad TC_{c, m} = \alpha_0 + \alpha_1 \ln(Age_{c, m}) + \alpha_2(Usage_{c, m}) + \alpha_3(Usage_{c, m})^2 + \varphi(\textbf{Market}) + \varepsilon,$$

where $Age_{c, m}$ and $Usage_{c, m}$ are the age and usage per station per week in flight of creative c in market m, and **Market** is a matrix of dummy variables representing observations from Sacramento, Chicago, Miami, and Minneapolis, respectively. α_0 through α_3 are coefficients to be estimated, and φ is a vector of market coefficients, also to be estimated. $TC_{c, m}$ is the cumulative effect of creative c in market m. Within each market, TC_c is obtained as in Equation 4, by means of the following formula ($\beta_{c\ell}$ is the coefficient of creative c at lag ℓ):

$$(7) \quad TC_c = \Sigma_{\ell = 0 \text{ to } n} \beta_{c\ell} / (1 - \Sigma_{j = 1 \text{ to } p} \lambda_\ell).$$

The coefficients from the analysis are presented and plotted in Figure 5. The results are not significant but are in the expected direction. We tested a variety of alternative measures of frequency, age, wearin, and wearout. None of the analyses provided robust, consistently significant estimates. Thus the results at present do not provide support for the two-factor theory of advertising response. One explanation is that we had only two years of data and only five markets (though we did have a sample size of 95 observations). The analysis might get more powerful as we add markets and longer series of data. Alternatively, the effects of wearin and wearout may be so small that they are dwarfed by other factors, such as the quality of the creative and the fit of the creative with the target market. Note that much of the prior research on wearin and wearout has been conducted in laboratory settings (see Pechmann and Stewart 1988). Perhaps the effects of advertising frequency are too weak to register in a field setting.

Analysis of Profitability. The firm recruits clients in each market and sets a goal of 15 customers a month. For this service, the firm charges $x. If the firm goes over that number, it earns no immediate benefit. If the firm consistently goes under that number it may lose the client, so the firm strives to meet its commitment of 15 referrals, even if it incurs the opportunity cost of going over that target. Thus profit is some complex function of referrals generated. For simplicity, we adopt a base fee structure that suggests that an average referral is worth $x/15 = $y.

The total effect of advertising is obtained from Equation 4. The dependent variable is measured in units, so the cumulative effect of advertising is in units of referrals. However, our analysis indicates that effectiveness varies by station. Thus we need to compute the profitability of each station rather than of advertising in general. Recall that the variables for the various stations capture the difference by

Figure 5
EFFECT OF CREATIVE AGE AND REPETITION ON EXPECTED REFERRALS
REGRESSION RESULTS (n = 95)

Dependent Variable: Cumulative Effect of Creatives

Variable*	Coefficient	t statistic
Log age in days	−.157	−.635
Usage per station per week in flight	.094	.270
Square of usage per station per week in flight	−.006	−.191

$R^2 = 4.9\%$.

*Coefficients for market dummy variables are not included in this table.

Effect of Creative Age on Expected Referrals

Effect of Creative Repetition on Expected Referrals
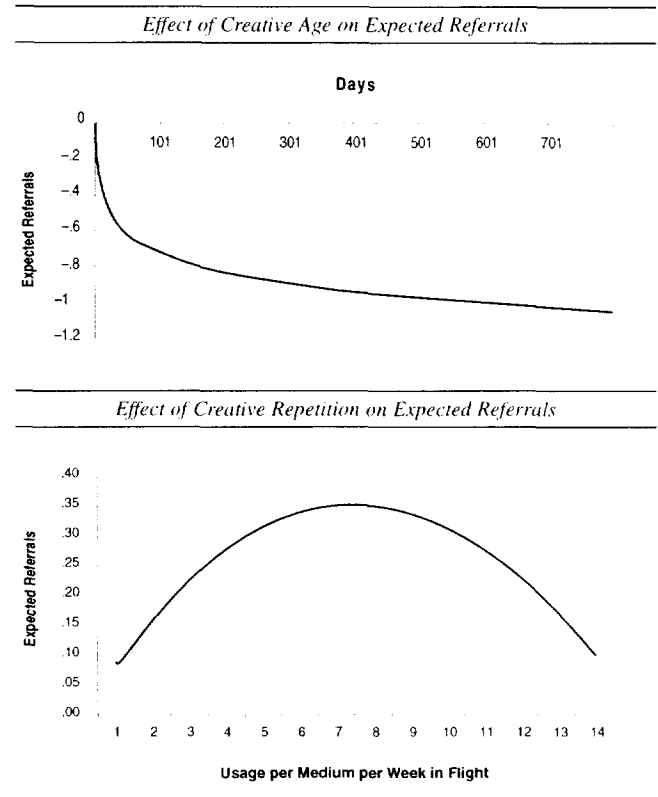
which a station has a higher or lower effect relative to the average effect captured by advertising in general. Moreover, because of the decay structure implied by the lagged values of the dependent variable, each of the stations has an implied lag structure and a cumulative effect that can be computed as in Equation 4:

$$(8) \quad TS_s = \Sigma_{\ell = 0 \text{ to } n} \beta_{s\ell} / (1 - \Sigma_{j - 1 \text{ to } p} \lambda_\ell),$$

where TS captures the effect of each station s, and $\beta_{s\ell}$ is the coefficient of station s at lag ℓ.

Thus the marginal revenue from advertising on a particular station is $y times the effect of advertising in general plus the unique effect of that station. The cost of advertising is the cost P_s of the buying time for the ad in that station. Thus the total profitability of advertising in station s is

$$(9) \quad \Pi_s = \$y \, (TA + TS_s) - P_s.$$

Table 5 presents the profits of advertising on various television stations. Note the wide variation in profits, which

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[5]We also tested for other forms of nonlinearity, but none fitted better than the expected ones.

Table 5

PROFITABILITY ($) OF STATIONS x TIME IN EACH MARKET

	Market				
	Sacramento	*Chicago*	*Miami*	*Minneapolis–St. Paul*	*Washington, DC*
Cost of average station x time*	172	452	202	203	198
Number of profitable stations x time	5	8	10	1	8
Profit from most profitable station x time	317	328	215	79	832
Number of unprofitable stations x time	67	42	28	45	35
Loss from least profitable station x time	–786	–2341	–400	–1672	–1800

*Note that the average cost listed here is the average cost of airing the ad across all stations in the market.

range from a loss of $2,341 in Chicago to a profit of $832 in Washington, DC, per ad at a particular time in a station. Indeed, this analysis seems to amplify the differences in the effectiveness of stations. The results suggest that buying time on the basis of the simple traditional rules of reach or frequency may not lead to profitable investments in advertising. Such rules deal only with cost per gross rating point of the medium itself. Traditional rules ignore exposure and response to specific ads for specific companies. Our analysis is based on consumer response to specific ads placed in specific media at specific times and accounts for profits generated by that response.

The profitability of various creatives can be computed in the same manner as that of stations. For the cost of advertising with a particular creative, we consider the average cost of the stations in which the creative appeared during the period under study. We present the results in Table 6. The analysis pinpoints which creatives are profitable in various markets and the precise level of profitability.

DISCUSSION

For decades modelers have tried to estimate the effect of brand sales using field data. In the past the challenge has been to overcome limitations in the data, primarily of collinearity from the contemporaneous effect of different marketing variables and of biases due to aggregate data. The availability of rich data has mostly reduced the severity of those problems while opening up new opportunities. The challenge facing researchers now is to address the age-old questions of advertising—which creative works, and when, where, and how often does it work? In particular, managers need a model to separate the effects of station and creative and to differentiate clearly between the current and carryover effects of advertising. We develop one model for this task in the context of direct advertising that leads to referrals for a medical service.

We first estimated an initial model with fewer explanatory variables using both transfer function analysis and regression. As we see it, transfer function analysis involves simple specification but very complex, tedious estimation. Regression requires careful, fairly complex specification but is easy to estimate. The results are similar by both methods. However, because we have fairly disaggregate data and a fairly complete specification of the key causal variables, our regression model did better than transfer function analysis. We therefore used multiple regression to estimate the full model. That analysis led to the following conclusions:

- Baseline referrals have a distinct temporal pattern that approximates a bell-shaped curve with respect to the hour of the day. The variation by hour is asymmetric and peaks at midmorning.
- Baseline referrals decline steadily by the day of the week.
- Advertising has significantly greater current and carryover effects than do baseline referrals.
- Advertising carryover decays rapidly and mostly dissipates within eight hours.
- The peak of the carryover effect generally occurs in the current hour for daytime advertising. The peak of the carryover effect generally does not occur in the current hour for morning advertising.
- Daytime advertising decay generally follows an exponential decay pattern, whereas morning advertising decay follows an inverted U-shaped pattern. These patterns are most distinct in more mature markets.
- Advertising effects differ substantially by station and creative. Many stations and creatives might not contribute to any increase in referrals.
- The age and usage level of creatives does not have a strong effect on creative effectiveness.
- Advertising response is similar across markets but stronger in larger markets.

Table 6

PROFITABILITY ($) OF CREATIVES IN EACH MARKET

	Market				
	Sacramento	*Chicago*	*Miami*	*Minneapolis–St. Paul*	*Washington, DC*
Average cost of airing a creative (across all stations in the market)*	172	452	202	203	198
Number of profitable creatives	11	0	5	0	0
Profit from most profitable creative	615	–72	402	–8	–9
Number of unprofitable creatives	23	8	19	19	10
Loss from least profitable creative	–260	–442	–414	–318	–375

*Note that the average cost listed here is the average cost of airing the creative across all stations in the market. It is not the cost of producing the ad, which is a sunk cost at the point of media scheduling.

•Even when advertising is effective, it may not be profitable. Indeed, highly profitable creatives and stations are few.

Besides these general conclusions, the model gives managers a strong analytical framework to estimate the role of advertising in promoting a service and evaluate its profitability fairly precisely. In particular, the model highlights creatives and stations that are highly effective versus those that are ineffective. More to the point, the analysis shows the level of profitability of the alternative creatives and stations and clearly indicates the direction managers should take. For example, in Sacramento, substituting an ad from the least effective station x time to the most would allow for a $1,103 increase in profitability per ad aired (see Table 5). The firm could easily test this prediction by airing an ad on the two alternative stations x times on comparable days of the week and noticing the change in referrals and estimated profitability.

For researchers the results underscore the value of disaggregate data, especially to determine the effects of creative, station, and time of the day. Moreover, the traditional focus on estimating general advertising effectiveness may no longer be justified given the availability of data on these specific issues and of the technologies to analyze them appropriately.

It is easy to point out limitations of the study, some of which could be worthwhile topics of further research. First, though the empirical setting provides a unique means of testing previously unexplored issues in advertising response, it also limits the generality of the study. The results from the study are only suggestive and not conclusive. Second, the model does not allow for time-varying parameters, which enable the effects of advertising or the other variables to increase or decrease by age of the market. Third, the model does not control for the effects of seasons, special holidays, and probable breakdowns in the service.

Fourth, the model does not consider the effects of advertising on attitude and memory. Behavioral research indicates that such effects from previous advertising could mediate response to current advertising. The firm neither has collected nor plans to collect information on attitude. Nevertheless, this would be an important avenue of research that could throw light on both the attitudinal effects of advertising in a field setting and the long-term dynamic effects of repetitive advertising. As a result, the analysis has a relatively higher probability of a type II error but a lower probability of a type I error. Managers should be wary that marginally unprofitable ads may still be profitable if we could somehow compute the long-term effects on attitude and memory. But they should balance this notion with recent evidence that suggests that if an ad has no impact in the short run, it is unlikely to have an impact in the long run (Lodish et al. 1995). Overall, profitable ads are probably worth further support, while clearly unprofitable ads are worth trimming.

Fifth, the current analysis of profitability is fairly simple, assuming a certain fixed value for each additional referral that advertising generates, irrespective of the client it benefits. This profit function, though common in most advertising contexts, does not precisely represent the current context. The actual profit function is a complex truncated function that varies by client: Although the shortfall in benefits may trigger penalties, stimulating referrals for a client beyond requirements of the contract has no immediate financial benefit. Thus, further research should consider opti-

mal referrals in response to advertising by client, given this stepwise profit function. Our profitability results are imprecise indicators of the actual profits.

Along these lines, a promising avenue of research would be to develop a model to allocate advertising dollars to time of day, station, and creative optimally, on the basis of the estimated response functions and profit per referral. This analysis could also be extended to allocation of advertising dollars across markets. These tasks would involve complex nonlinear optimization. A final promising avenue of research is to explore characteristics of creatives and stations that are responsible for the differences in their effectiveness.

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