Research On Effectiveness Of Agricultural Commodity Promotion

Proceedings from Seminar
Arlington, Virginia

April 9-10, 1985

Sponsored by

Farm Foundation
Agricultural Marketing Service, USDA
Economic Research Service, USDA
Foreign Agricultural Service, USDA

EVALUATING ADVERTISING EFFECTIVENESS USING TIME SERIES DATA

Henry W. Kinnucan
Auburn University

Time series data form the basis for much of the empirical evidence relating to advertising effectiveness. In addition, many of the questions that managers of promotional funds seek to answer regarding appropriate allocation of promotional resources across markets, media, products, and time appear to be especially amenable to analysis with these type of data and their associated models. As such, those interested in advertising and promotion, whether it be from a public policy, research, or private decision making perspective, have a stake in being knowledgeable about the use of time series analysis in the evaluation of advertising and promotion effectiveness: its comparative advantage relative to other evaluation techniques, and its limitations in terms of providing the kind of decisive information often requested of such analysis.

The purpose of this paper is to discuss time series analysis of advertising and promotion from three vantage points: methodological developments that appear useful in obtaining improved empirical measures of the sales-advertising relationship, data requirements that would provide the basis for meaningful and accurate analysis, and conceptual issues associated with measurements of advertising response. In discussing each of these aspects, emphasis is placed on technical problems commonly encountered in applied work rather than theoretical issues, although the latter may have important implications for empirical analysis.

The paper proceeds by first discussing methodological developments relevant to model development. Measurement error and other data considerations are then discussed. Two conceptual issues, response asymmetry and "bracket creep," are addressed in the third section of the paper. A brief summary and conclusion closes the paper.

Methodological Developments

Using time series data to address various issues associated with advertising and promotion of farm products is seldom straightforward. Choices must be made regarding appropriate theoretical framework (if one exists), model specification, and estimating procedures. This section elaborates on a previous paper [22] and discusses methodological aspects of these issues found to be useful in applied analysis. These issues include choice of functional form, modeling carry-over effects, controlling for confounding influences, and seasonality effects.

Choice of Functional Form

Selection of the appropriate mathematical relationship between advertising and the sales variable is an important factor bearing on the quality of the effort to evaluate commodity promotional efforts. The literature on advertising effects is virtually unanimous in describing advertising as having a diminishing marginal effect on sales. (Simon and Arndt [32] review more than 100 studies and conclude that the sales-advertising relationship is characterized by diminishing marginal returns.) This finding means that one commonly used functional form — the linear — can be rejected out of hand because it implicitly assumes that the marginal product of advertising is constant throughout the range of advertising expenditure.

In addition to satisfying theoretical restrictions, a selected functional form should provide an accurate statistical fit to the data and provide for simplicity of computation [12]. Commonly used functions in food demand analysis that satisfy these criteria and permit marginal returns of advertising to diminish with increased expenditure are the logarithmic, the semilogarithmic, the log-inverse, and the inverse forms. A detailed review of each of these functional forms in the context of measuring advertising effects is discussed elsewhere [19]; therefore, let it suffice here to illustrate with an empirical example the implications of functional form selection. Milk sales-advertising response surfaces generated by the logarithmic (log-log) and the log-inverse form for the Buffalo, New York, market based on 1978-81 monthly data are presented in Figure 1. The two graphs show the log-inverse equation exhibiting a more marked sales response at lower levels of advertising (up to 30¢ per person per year on an annual basis) but as advertising continues to increase, the incremental sales response diminishes at a rapid rate compared to that of the logarithmic equation. In other words, the log-inverse form implies an advertising effect that is subject to rapidly diminishing marginal returns; whereas, the logarithmic form implies marginal returns that decline at a much slower rate. Which form is most appropriate depends on the nature of the particular problem. In the above case, my preference is the log-inverse form because most studies show the effectiveness of milk advertising diminishing rapidly as promotional expenditure for fluid milk increases [see e.g., 8].

The actual functional form chosen importantly influences results relating to optimizing behavior. For example, in the above case, if one believes that the logarithmic equation more nearly depicts the true

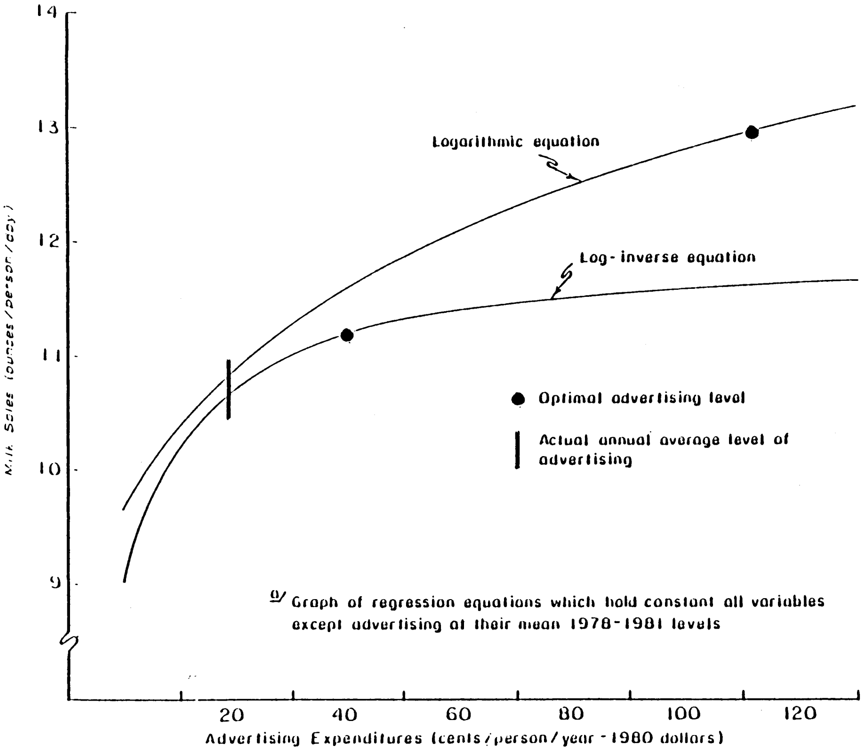

Figure 1. Milk sales - advertising response surfaces[a] generated by alternative functional forms of the advertising response function, Buffalo, New York.

relationship between milk sales and (generic) advertising, then the short-run profit maximizing level of expenditure (defined as the point where the marginal cost of advertising equals marginal producer revenue) is about $1.20 per person per year (compared to an actual expenditure of about 25¢ per person per year). The log-inverse equation, by contrast, implies an optimal expenditure level of about 50¢ per person per year. The magnitude of these differences highlights the importance of careful functional form selection when evaluating promotional programs. It suggests that the relative *rapidity* with which the chosen functional form permits the marginal effect to decline is of special importance.

Modeling Carryover Effects

That advertising continues to affect sales beyond the original period of expenditure is well established in the literature [36, 18, 29, 35, 6]. To accurately quantify the notion that "... old advertisements never die — they just fade away" [36, p. 367] is another matter, and one that poses special problems to those attempting to evaluate commodity promotional programs. In an econometric framework, the estimation issues center around finding the most statistically efficient method of capturing the essence of the lag structure, while at the same time minimizing bias. In order to accomplish this, the researcher needs some *a priori* notion of both the shape and the length of the "decay curve" (to use Waugh's terminology). Unfortunately, the theoretical literature to date [see e.g., 28, 30] has not provided much guidance in this respect; hence, prior empirical results have had to serve as the primary basis for making these critical decisions.

With regard to lag length, in an extensive review of the empirical literature covering some seventy studies, Clarke [6, p. 355] concluded that " . . . 90% of the cumulative effect of advertising on sales of mature, frequently purchased, low-priced products occurs within 3 to 9 months of the advertisement." This conclusion is supported by recent work done at Cornell in connection with ongoing evaluation of the New York State Dairy Promotion Order. Studies of generic advertising of fluid milk conducted in two different cities, Buffalo and New York, indicate lag lengths of six months [23, 19] a study of yogurt advertising in California indicates a lag length of seven months or less for branded and generic advertising [13]. These results contrast sharply with those of Nerlove and Waugh who found a decay period of ten years for orange advertising. One should note, however, that the Nerlove and Waugh results are based on annual data, which are likely to give upward biased estimate of the true lag length, as demonstrated by the analysis of Clarke. (To avoid "data interval bias" in the estimation of advertising effects, Clarke [6] recommends the use of *monthly* data in most situations.) This point is discussed in more detail below.

Theory relating to the shape of the decay function is also sparse and not well developed. Early thinking on the shape of the advertising response function centered around the notion of a monotonically declining effect; i.e., advertising achieving its greatest response in the initial period and thereafter tapering off in an exponentially declining fashion [36 and 29]. However, recent thinking on the causes of the delayed response to advertising suggest a "decay" function that may require time to build before the decay process can begin. For example, Jastram [18] indicates two reasons for a delayed response to advertising: (1) magazines or newspapers in which ads are placed may not be read until sometime after the ads are paid for and (2) "it takes time for people to get around to buying" [11, p. 40]. Presumably, the decay process itself is related to "the remembering and forgetting of advertising" [39].

Recent analyses of various dairy product promotional programs based on monthly data support the notion of a hump-shaped lag pattern [see e.g., Kinnucan 23, 19 and 13, 34]. The estimated lag structures from these studies show the initial period response being small in relation to the total response and the peak effect occurring two to four months beyond the initial expenditure (Figure 2). These findings are consistent with those of Bass and Clark [3] which show that some period of time is required for advertising to build to its maximum effectiveness.

In the above discussion, advertising is implicitly thought of as entering the demand model in distributed lag form with the idea that sales respond to advertising slowly over time because of psychological and other impediments to change. An alternative view is to think of advertising as a stock variable which is subject to depreciation over time. This approach defines a variable in the demand function as "goodwill" which " . . . summarizes the effects of current and past advertising outlays on demand" [30]. Although the stock (or goodwill) approach has intuitive appeal in that it views advertising as creating an "intangible demand-generating variable representing an accumulated effect of prior advertising expenditure" [28, p. 823], it has the disadvantage of requiring an unknown decay function to be specified *a priori*. Nevertheless, the concept has proved useful in a number of

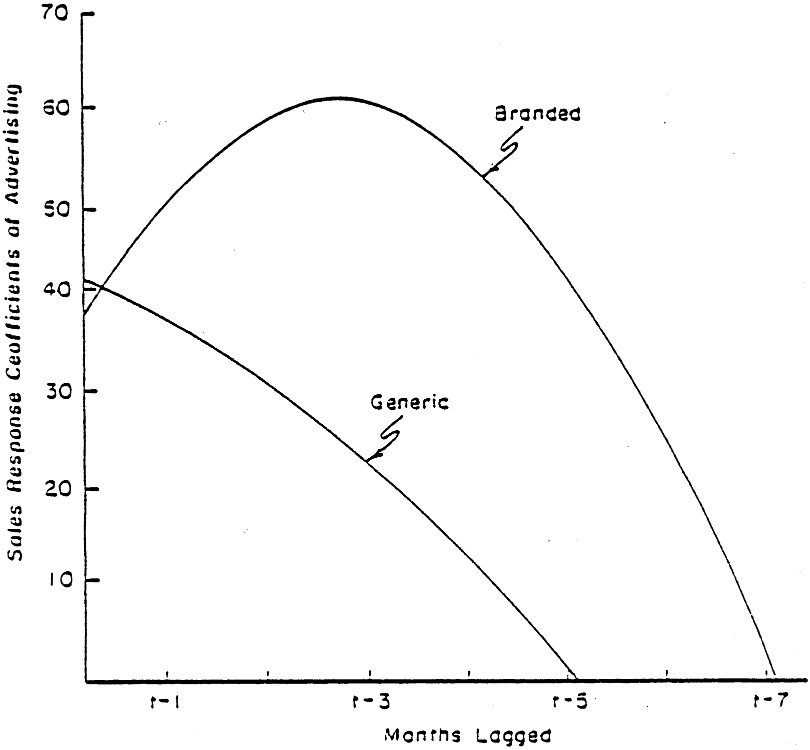

Figure 2. Decay structure for branded and generic advertisement expenditure, California

Source: Hall, L. and I. Faik. "The Effectiveness of Generic Versus Brand Advertising for Manufactured Milk Products - The Case of Yogurt." Cornell Agricultural Economics Staff Paper No. 82–4, April 1982.

theoretical and empirical settings [see e.g., 21, 19 and 28 and the references cited therein] and thus will likely serve as a significant contribution to time series modeling of advertising behavior.

Controlling for Confounding Influences

An important measurement problem associated with time series analysis of commodity promotional programs is that of controlling for confounding influences such as income, population, price, and demographic changes. In econometric terms this means specifying the demand equation to include all relevant explanatory variables. Econometric theory tells us that estimated coefficients of advertising variables will be biased if relevant explanatory variables (which are correlated with advertising) are omitted from the estimating equation [see e.g., 31]. Because economic variables tend to be highly correlated with one another, the need to include all relevant economic variables in the demand model creates a dilemma for the researcher: omitting a relevant variable from the demand equation may bias the advertising coefficient, but including it may lower the precision (accuracy) of the estimated advertising effect. Thus, the researcher must decide from a possible plethora of demand shifters which ones can be safely ignored in terms of minimizing bias and improving the precision of estimated advertising effects.

The importance of correct model specification can be illustrated with results obtained for New York City market relating to a generic advertising fluid milk campaign conducted there since 1971. Econometric analysis based on monthly data for the period January, 1971, through June, 1980, provides an estimate of the long-run advertising elasticity of 0.051 which is statistically significant at the 5% level [23]. Two factors that importantly influence milk consumption are age and race: people drink less milk as they grow older and blacks consume less milk than others. In New York City, the nonwhite proportion of the population grew by 20% over the study period and the less than age 20 proportion of the population (the heavy milk consuming age group) shrank by 13%. When these two variables are omitted from the demand equation, the estimated long-run advertising elasticity becomes 0.040 — a downward bias of 30%. Thus, if demographic factors are ignored, econometric analysis understates the true impact of the advertising effort.

Seasonality Effects

Many food products are subject to seasonal shifts in consumer preferences. This means that in time series modeling, to avoid specification error, allowance must be made for intrayear demand shifts. A common approach is to include dummy variables in the model which permit the demand function to shift in a parallel fashion with the seasons. Although dummy variables are easy to use and provide a statistically precise means of handling seasonality, they have the disadvantage of consuming a relatively large number of degrees of freedom, especially when monthly data are used. Doran and Quilkey suggest using the harmonic variable format as an alternative to monthly dummies when the seasonal demand for the good in question follows a regular pattern from year to year [9]. Harmonic variables, which are constructed as simple sine and cosine functions of trend, have the advantage of simplicity in that usually only two to four variables are needed to capture intercept shifts compared to the eleven variables needed when dummy variables are used.

Harmonic variables have been found to be especially useful in cases where interaction effects between advertising and seasons are thought to be present. For example, milk consumption in New York City increases in the spring months and reaches a nadir during the summer months of July and August. Since consumers appear to be less interested in drinking milk during the summer than at other times of the year, it may be that milk advertising is less effective during summer than at other times. One way to test this hypothesis in an econometric framework is to specify monthly dummies both in linear form and in multiplicative form with the advertising variable serving as the multiplicand. In addition to the degrees of freedom problem associated with this approach, multicollinearity between intercept and slope dummies becomes a problem. Using harmonic variables to capture the intercept changes, while retaining the use of dummy variables to indicate slope changes, mitigates the multicollinearity problem while simultaneously conserving degrees of freedom. This approach was adopted in a study of fluid milk advertising in New York City with the result indicating significant seasonal differences in the ability of advertising to influence milk sales [21].

Whether using harmonics or dummy variables to indicate seasonal variation in the model, it is important to understand the nature of the ensuing multicollinearity and implications for hypothesis testing. Multicollinearity arises when intercept and slope shifts are simultaneously specified in a model because both variables have nonzero values in the same time periods and zero values in all other time periods. The extent of the multicollinearity can be gauged using the formula worked out by Wildt [37, p. 38]:

$$r = \left[\frac{n-1}{(v^2 n + n - 1)} \right]^{1/2}$$

where r = the expected value of the correlation coefficient between slope and intercept dummy variables, n = the number of seasons, and v = the coefficient of variation of the dummy slope variable (computed by using only the nonzero values). This simple formula yields two useful (and not surprising) facts: multicollinearity in a seasonal model can be reduced by reducing either the number of "seasons" or by increasing the intraseasonal variation in the slope variable. Thus, for example, if $v=1$ and monthly data are being used, the researcher may choose to specify quarterly rather than monthly shifts, in which case collinearity would be reduced 74% (from r = .23 to r = .06). To increase the value of v, Wildt suggests using multiple observations of the decision variable per unit of time obtained from cross-sectional data. He argues that this approach is "suitable" if four conditions are met if 1) no cross-sectional variation exists in the model parameters, 2) variables of concern can be measured separately for a number of different market areas, 3) the separate markets are quite similar, and 4) levels of decision variables of interest vary considerably across markets.

Methods described by Ladd [25] and more recently by Wildt [37] provide theoretically straightforward testing procedures for determining the presence of seasonal slope and intercept effects. However, the multicollinearity inherent in full seasonal models often leads to indeterminant results when these tests are applied to actual data. Nonetheless, the inclusion of seasonal variables in models of market response may have significant decision implications [11] and hence need to be carefully considered.

Data Requirements

Time series analysis of advertising effectiveness requires the existence of a quality data base. Fundamental elements affecting quality include absence of measurement error, adequate variation in the data (particularly with respect to advertising), sufficient number of observations, appropriate time interval, and sufficient auxiliary detail regarding changes in media mix, copy, and advertising costs over the sample period. Each one of these elements is discussed in some detail below.

Measurement Error

Measurement error in model building occurs when data fail to depict accurately the theoretically correct definition of specified variables. Inaccuracy may arise either because errors were made in the collection and collation of the data or because available data do not match the theoretical constructs. The former source of error may seem easy to avoid by careful monitoring of data collection procedures. However, in an advertising setting oftentimes one needs data limited to a particular geographical area. This poses the problem of accurately accounting for product inflows and outflows relative to that region. In addition, expenditure measures of advertising specific to a particular "market" might not be well-correlated with actual strength of the advertising signal because of unmeasurable "spill-in" effects from neighboring markets or because of changes in media mix (if data is aggregated across media) and advertising copy within the sample period. An appropriate advertising cost index in which to deflate advertising expenditures can be difficult to construct, particularly if the costs of different media are changing at different rates over time. The problem of media cost index construction is exacerbated when localized market responses are being studied because media costs differ significantly across regions depending on the size and demographic characteristics of the particular market. If the market being studied is "small," information needed to construct a market-specific index is typically lacking, forcing the researcher to use a national or other index which may bear only a semblance to actual local media costs.

Measurement error associated with a lack of correspondence between the theoretically correct definition of a variable and its empirical counterpart is a danger when one takes the "goodwill" approach to modeling advertising effects. As defined by Nerlove and Arrow [30], goodwill is a stock which represents the cumulative effect of past and current advertising outlays on demand. Implicit in the definition is an assumption of an infinite lag with an unknown decay structure. Choosing an appropriate decay mechanism to indicate how goodwill depreciates over time is necessary to avoid this type of measurement error.

The problem of ascertaining the appropriate empirical definition of "goodwill" in the advertising context recalls the problem of measuring "permanent income" in the context of Friedman's [10] Permanent Income Hypothesis. The striking similarities in the two concepts create the possibility that the rich literature of the Permanent Income Hypothesis can be exploited to the benefit of our understanding of advertising effects. For example, questions concerning the effectiveness of "pulsing" or "flighting" advertising might be addressed by separating goodwill into permanent and transitory components. The statistical significance of the marginal sales response to "transitory" advertising would serve as evidential support for or against pulsing.

Consequences of measurement error for obtaining "good" estimates of model parameters are well worked out in the econometric literature [see, e.g., 27, p. 292f]. The chief result is that if an *independent* variable is measured with error, then the estimated parameter associated with that variable is unambiguously biased *downward* in absolute value. This result implies that if the advertising or goodwill variable contains measurement error, our estimates of the advertising effect will be too conservative, which may be of some comfort. Less comforting is the fact that measurement error in even one independent variable of the model results in biased estimates of all model parameters. Moreover, the *direction* of the bias for coefficients whose variables are measured without error is indeterminant. In other words, if advertising is measured with error, estimated income and price effects obtained from the model are likely to be either too large or too small even though these latter variables are measured correctly.

Bias introduced into ordinary least squares (OLS) regression estimates by measurement error can be minimized by ensuring that the independent variable has adequate variation. What is "adequate" can be illuminated by the following simple exposition of the errors-in-variables model. Suppose that the true model is

$$s = Ba + e \tag{2}$$

where s = sales, a = advertising and e = error term satisfying the Gauss-Markov assumptions for BLUE estimators. Assume that advertising is measured with error so that $a^* = a + u$ where u represents measurement error with an expected value of zero and constant variance. Our estimation equation becomes

$$s = Ba^* + w \tag{3}$$

Applying OLS to equation (3) yields a biased and inconsistent estimate of B because of correlation between a^* and w. The expression for the bias is as follows [27, p. 293]:

$$plim\ \hat{B} = \frac{B}{1 + \sigma_u^2/\sigma_a^2} \tag{4}$$

where σ_u^2 and σ_a^2 represent variance of u and a respectively. As can be seen, as σ_a^2 grows relative to σ_u^2, $\hat{B}$ becomes a better estimate of its true value. The message here is that getting lots of variation in our advertising data can help mitigate the effects of measurement error.

It is interesting to note in passing that econometric theory suggests that measurement error in the dependent variable is innocuous with respect to parameter estimation. As long as observational errors in the dependent variable are random, a correlation between the independent variables and the error term in the model will not arise. Theil [33, p. 609] provides some intuition for this result by noting that the OLS method works by minimizing the sum of squared errors in the vertical direction, i.e., discrepencies in the dependent variable. Thus, errors associated with measurement became indistinguishable from errors associated with random shocks. This result implies that in a limited resource environment greater emphasis should be placed on obtaining good measures of advertising than of sales.

Variation in Advertising Data

The success of econometric procedures applied to time series data in providing useful and defensible results relating to farm commodity promotional programs will hinge to an important degree on the amount and type of variation in the advertising data. The fact that these expenditures are under the direct control of producer groups means that a certain amount of latitude can be exercised in ensuring adequate variation. Adequate variation in the advertising data does a number of things: (1) it reduces the problem of collinearity with other explanatory variables thereby increasing the precision of the estimated advertising effect, (2) when the advertising effect is specified in distributed lag form, it reduces the collinearity among lagged regressors, resulting in better estimates of the advertising decay pattern, (3) it permits the estimated response function to have greater versatility in that a wider range of advertising levels can be studied, (4) it increases the chances of detecting significant seasonal variation in advertising effectiveness and, as discussed above, (5) it reduces bias associated with measurement error.

In planning for adequate variation in the advertising data, two econometric factors need to be considered. First, zero observations potentially limit the number of functional forms that can be used to model the sales advertising relationship. For example, division by zero is not possible and the logarithm of zero does not exist; hence, logarithmic and inverse forms are eliminated from consideration unless a goodwill specification is used. Thus, months of zero advertising expenditure should be avoided. Secondly, simultaneous equation bias can become a problem if advertising is timed to coincide with seasonal changes in sales. In the private sector, many firms appear to use a fixed sales to advertising rule which raises the question of direction of causality between the two variables. Failure to address simultaneity in the determination of sales and advertising can result in biased or, what is worse, spurious regression results [1, 4]. To avoid this problem, advertising expenditures must vary in such a way that seasonal changes in sales volume are not intentionally made to correlate with advertising *ex ante*.

It is recognized that in advocating a random variation advertising policy that is bounded from below at some positive (non-zero) amount, a certain amount of efficiency in the investment might be sacrificed. For example, the Nerlove and Arrow theoretical model indicates a constant advertising to sales ratio to achieve maximum effectiveness and empirical evidence supports this result [21, 39]. However, the tradeoff is that the quality of evaluative evidence available to policymakers and other interested parties relative to the efficacy of the promotional program will be improved. In the initial stages of an advertising initiative, it may be especially useful to have results that engender confidence in the program.

Number of Observations

In a time series context an elementary requirement is that sufficient number of observations exist to estimate model parameters. The requirement of relatively rapid feedback on program effectiveness can make data availability a limiting factor in initial attempts to evaluate new commodity promotional programs using time series data. Or, if one is attempting to estimate a model containing both slope and shift variables, data requirements expand. A rule of thumb suggested by Belsey *et al.* [5] to indicate the minimum number of observations necessary to estimate a particular regression equation is $N > 2.5P$, where N = number of observations and P = number of parameters to be estimated. Thus, if our model contains nine independent variables and a constant term we will need at least twenty-five observations to estimate the parameters. If data are too few, regression estimates of advertising effects are liable to be unstable and sensitive to "extreme" observations.

Time Interval

In using time series data to estimate sales-advertising relationships the researcher must decide which time interval of data to use, e.g., monthly, quarterly, or annual. In the econometric literature this problem is referred to as aggregation over time. Time aggregation is an especially important issue in models containing a distributed lag because choosing an inappropriate time interval can lead to large systematic biases, especially in estimates of the length of the lag [See 27 and references cited therein].

Choosing an appropriate data interval depends on knowledge of the "reaction interval" of the economic units under study. If the effects of advertising are known to completely dissipate within thirty days of exposure, then applying a distributed lag model to annual, quarterly, or even monthly data would obviously be inappropriate (but weekly data could be used). In this case the reaction interval is one month; using data with a time interval longer than the reaction interval would likely lead to overestimation of the distributed lagged effect.

In an extensive survey of the econometric literature on advertising effects, Clarke concludes that annual data should *not* be used to study advertising effects: "There is a bias in the estimate of the coefficient of lagged advertising as well as the estimate of the implied duration interval." [6, p. 356]. Annual data tend to significantly overstate the length of the lag distribution. On the other hand, using weekly data may result in downward biased estimates of the lag length, especially if the purchase cycle of the product under study is longer than one week [6, p. 355]. After making adjustments for the data interval bias Clarke concludes ". . .the published econometric literature indicates that 90% of the cumulative effect of advertising on sales of a mature, frequently purchased, low-priced product occurs within 3 to 9 months of the advertisement. The conclusion that advertising's effect on sales lasts for months rather than years is strongly supported." [6, p. 355]. A basic conclusion of the study is that monthly data are likely to represent the most appropriate time interval for most time series studies of advertising response.

Auxiliary Detail

Oftentimes advertising data are provided to the researcher without information relating to the "flesh and blood" details of the advertising campaign that may either later prove useful in interpreting regression results or be helpful in initial model specificiation. If the data relate to a time period of, say, three years (which may be considered a minimum time period in which to conduct an analysis using time series data) it is likely that a number of changes regarding the advertising effort have taken place. Target groups to which the commercials are directed may have changed; advertising creatives or themes usually evolve over time; a change in the advertising agency may occur; the advertising agency may have periodically purchased media time or space at significant discounts; and, if data are aggregated across media, significant or regular changes in the media mix over time may have occurred. Having access to these kinds of details can improve the econometric modeling of advertising phenomenon and provide for a more informed interpretation of results.

Conceptual Issues

Asymmetry in sales response to advertising and "bracket creep" in optimal advertising levels are two conceptual issues that merit attention in the times series analysis of advertising effects. Each of these issues is developed in some detail below.

Response Asymmetry

The notion that economic agents respond differently to increases versus decreases in economic stimuli has strong intuitive appeal and has received empirical documentation in studies of pricing behavior, demand, and supply response [17, 14, 38, 20]. In an extensive review of empirical literature on advertising effects, Little reaches the conclusion that a similar asymmetry is likely to be present in the market response to advertising: "Sales respond dynamically upward and downward to increases and decreases of advertising and frequently do so at different rates" [26, p. 644]. The nature of the asymmetry is hypothesized to be such that sales respond relatively rapidly to increases in advertising, but decay rather slowly when advertising decreases (see Figure 3). The fast upward response is thought to be related to the learning process that takes place when advertising is increased. Three stages can be identified: (1) hearing or seeing the advertising message, (2) absorbing it, and (3) acting on it. Because as few as three exposures may be enough to stimulate action [24], the sales response to increased advertising exhibits a concave shape when plotted against time. The initial rapid burst in sales occurs as nonusers are enticed to buy the product. Nonusers may be of two types: those who are un-

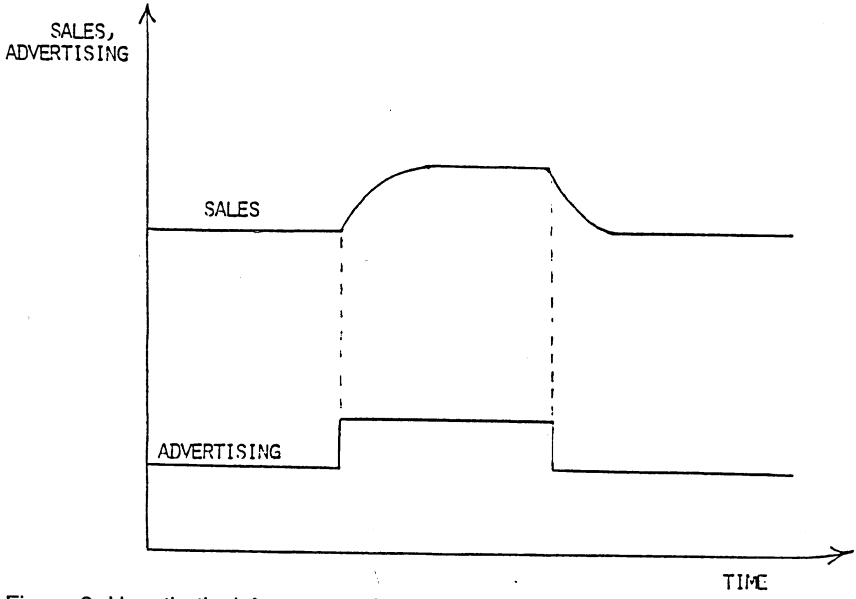

Figure 3. Hypothetical Asymmetry in the Sale Response to Advertising.

familiar with the product and those who know of the product, but, for one reason or another, are not purchasing it. Advertising encourages the former group to buy the product by informing them of the product's existence and merits. The latter group may be encouraged to buy the product for the sake of reexamination of the product's characteristics or simply for variety.

Sales decay slowly as advertising is withdrawn because now the process is being governed by the consumers' experience with the product, the rate at which advertising is forgotten, competitive advertising, and other factors. New purchasers who have bought the product for its novelty or variety and those who are only marginally impressed with the product are likely to exit the market once the reinforcing effect of advertising recedes. If the rate of forgetting advertising follows an exponential decay process as suggested by Zielske [39], a convex time pattern for sales would occur.

Considering the above, Little argues "...a good model of sales response to advertising should permit different rise and decay rates" [26, p. 637]. The methodology for following such advice in a time series context has been worked out [17, 38] and the implications may be important for advertising and promotion policy. For example, if the slower decay rate associated with decreases in advertising expenditures imply smaller advertising elasticities, then estimates of advertising effect that neglect asymmetric sales response may overstate the effectiveness of the program, especially in instances in which real advertising expenditure is declining over time. By the same token, in initial stages of a new advertising and promotion initiative when real expenditures are expanding rapidly, measurements that fail to permit rapid sales impact may understate actual short-term effectiveness. The eight years of monthly data available for the New York City market in which real per capita generic advertising expenditures for fluid milk increased from 5.7¢ per capita to 9.5¢ between 1972 and 1975 and then declined steadily to 4.7¢ per capita in 1979 appears to afford the opportunity of testing the hypothesis that advertising elasticities differ depending on whether expenditures are rising or falling.

Bracket Creep

Oftentimes the available time series data on advertising expenditures are restricted to a narrow range of expenditures. In the case of generic advertising campaigns conducted by agricultural commodity groups, a further limitation of the data may be that the maximum amount spent on advertising during any given time interval may be well below what would be considered "optimal" in terms of maximizing private returns on the advertising investment. As a result, empirical sales response functions generated by these data may be deficient in that they are incapable of indicating the true global optimum expenditure level. Instead, pseudo-optimal expenditure levels are indicated which are in fact captive of the data range used in estimation and the functional form imposed on the sales-advertising relationship. Because available data do not include the "true" optimal level of expenditure (and ideally go beyond that level of expenditure) these pseudo-optimums tend to understate the true optimum.

The possibility that measured sales response functions understate true optimum investment levels when advertising data fail to exhibit adequate variation in the upper ranges of advertising investment is illustrated in Figure 4. Curve w shows the true sales response function given advertising expenditure range AB. The optimum expenditure level based on this curve (computed as the point where an additional dollar of advertising exactly yields one additional dollar of revenue to the advertising group) is a^*. Curves u and v are empirically determined sales response functions that are measured without the benefit of the full range of advertising expenditure. Each one of these curves approximate the true global curve within the range of available data. However, because of the way in which data interact with functional form to govern the behavior of the marginal product of advertising, estimated optimum expenditure levels differ for the two curves. Curve u, which is based on a relatively low level of advertising expenditure, gives a lower computed optimum (a') than curve v, which is based on a higher expenditure range. Because both curve u and curve v "see" only a portion of the relevant range, they understate the true optimum.

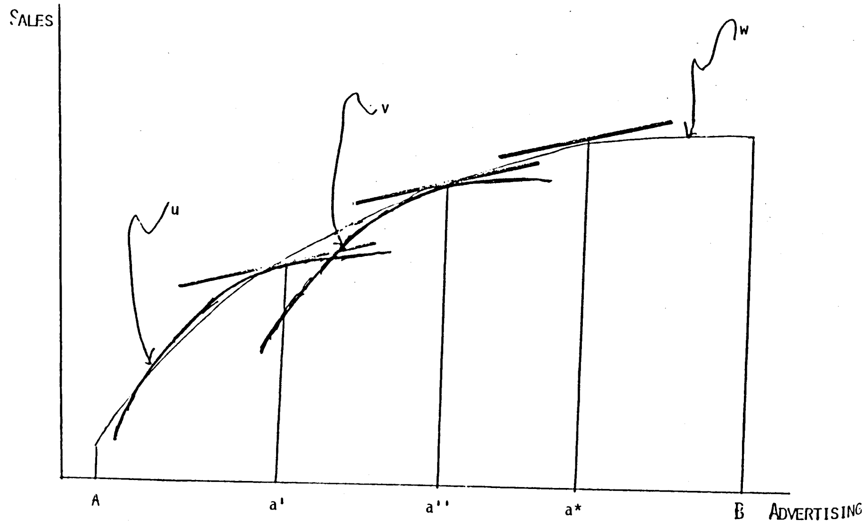

Figure 4. Hypothetical Illustration of "Bracket Creep" in Empirically Determined Optimal Advertising Levels.

The above phenomenon, which I have termed "bracket creep" because computed optimum expenditure levels increase as the level of advertising increases, may also be a problem when attempting to compare the relative effectiveness of different media or the effectiveness of advertising campaigns across markets. Curve *u* might represent expenditure on "hard" media advertising (newspapers, magazines, billboards and buses), curve *v* expenditures on radio advertising and curve *w* expenditures on television advertising. If the estimated response function for television advertising "sees" a greater portion of the true curve than, say, radio advertising, then "optimum" television expenditures are likely to be overstated relative to "optimum" radio advertising. In other words, television advertising may appear more effective than radio or print media advertising simply because it receives a greater range of expenditure than the other media over the sample period. An analogous result could occur if markets with widely differing levels of advertising exposure are being compared. The bracket creep phenomenon would favor the market with the higher expenditure level, *ceteris paribus*.

Summary and Conclusions

This paper discusses methodological developments, data requirements, and conceptual issues associated with using time series data to evaluate effectiveness of farm commodity promotional programs. A general conclusion is that such analyses have in the past and will continue to provide useful input in the decision making process regarding the efficacy of farm funded promotional programs. However, to ensure quality evaluative evidence flowing from such analyses, researchers will need to keep abreast of innovations in research methodology, emphasize the importance of obtaining "good" data, and be creative in dealing with conceptual issues like response asymmetry and "bracket creep" discussed in the text.

Of particular importance is the need to stress the crucial role that adequate, i.e., "lots of," variation in the advertising data can play in obtaining good statistical results from time series data. Cooperation between individuals charged with managing promotional funds and researchers attempting to verify program effectiveness can result in program design that meets the needs of both parties. Beyond data variation, greater research emphasis needs to be placed on appropriate mathematical forms to express the relationship between advertising and sales. The sensitivity of results relating to optimal allocations of scarce promotional funds to functional form selection begs that the issue receive a more systematic treatment in our research efforts.

REFERENCES

[1] Ashley, R., C.W.J. Granger, and R. Schmalensee. "Advertising and Aggregate Consumption: An Analysis of Causality." *Econometrica.* 48(1980):1149–1167.

[2] Ball, R.J. and R. Agarwala. "An Econometric Analysis of the Effects of Generic Advertising on the Demand for Tea in the U.K." *Brit. J. Mkting.*, no. 4 (Winter 1969), pp. 202–217.

[3] Bass, F.M. and D.G. Clarke. "Testing Distributed Lag Models of Advertising Effect." *J. Mkting. Res.* 10 (1972):298–300.

[4] Baumol, Wm. J. *Economic Theory and Operations Analysis.* Englewood Cliffs NY: Prentice Hall, 1977.

[5] Belsey, David A., et al. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity.* New York: John Wiley and Sons, 1980.

[6] Clarke, D.G. "Econometric Measurement of the Duration of Advertising Effect on Sales." *J Mkting. Res.* 13(1976):345–357.

[7] Clement, W.E. and P.L. Henderson. *Consumer Response to Various Levels of Milk Advertising for Fluid Milk.* USDA ERS Mkting. Res. Rep. 805, Oct. 1967.

[8] Clement, Wendell E. "Some Unique Problems in Agricultural Commodity Advertising." *J. Farm Econ.* 45(1963):183–194.

[9] Doran, H.E. and J.J. Quilkey. "Harmonic Analysis of Seasonal Data: Some Important Properties." *Amer. J. Agr. Econ.* 54(1972):646–651.

[10] Friedman, Milton. *A Theory of the Consumption Function.* London: Oxford University Press, 1957.

[11] Green, Richard D. and John P. Doll. "Dummy Variables and Seasonality." *Amer. Stat.* 28(1974):60–62.

[12] Goreux, L.M. "Income and Food Consumption." *Monthly Bull. Agr. Econ. and Stat.* 9(1960):1–13.

[13] Hall, Lana and Ingrid Foik. "The Effectiveness of Generic Versus Brand Advertising for Manufactured Milk Products - The Case of Yogurt." Dept. Agr. Econ. Staff Paper No. 82–4, Cornell University, April 1982.

[14] Heien, Dale M. "Markup Pricing in A Dynamic Model of the Food Industry." *Amer. J. Agr. Econ.* 62(1980):10–18.

[15] Henderson, P.L. "Butter and Cheese: Sales Changes Associated with Three Levels of Promotion." USDA ERS Agr. Econ. Rep. 322, Jan. 1976.

[16] Henderson, P.L., J.F. Hind, and S.E. Brown. "Sales Effect of Two Promotional Themes." *J. Adv. Res.* 1(1961):2–11.

[17] Houck, J.P. "An Approach to Specifying and Estimating Nonreversible Functions." *Amer. J. Agr. Econ.* 59(1977):570–572.

[18] Jastram, Roy W. "A Treatment of Distributed Lags in the Theory of Advertising Effect on Sales." *J Mkting. Res.* 13(1976):345–357.

[19] Kinnucan, H.W. "Media Advertising Effects on Milk Demand: The Case of the Buffalo, New York Market." Dept. Agr. Econ. Research 83–13, Cornell University, February 1983.

[20] Kinnucan, H.W. and O.D. Forker. "Asymmetry in the Retail Pricing of Major Dairy Products with Implications for U.S. Dairy Policy." Dept. Agr. Econ. Staff Paper No. 84–14, Cornell University, May 1984.

[21] ________. "Seasonality in the Consumer Response to Milk Advertising: Implications for Milk Promotional Policy." Dept. Agr. Econ. Research 82-29, Cornell University, Sept. 1982.

[22] Kinnucan, Henry. "Evaluating Farm Commodity Promotional Programs." Paper presented at annual meeting of the AAEA, Ithaca, N.Y., 5–8 Aug. 1984.

[23] Kinnucan, Henry W. "Demographic Versus Media Advertising Effects on Milk Demand: The Case of the New York City Market." Dept. Agr. Econ. Staff Paper 82–5, Cornell University, March 1982.

[24] Krugman, H.E. "Why Three Exposures May Be Enough." *J. Adv. Res.* 12(1972):11–14.

[25] Ladd, G.W. "Regression Analysis of Seasonal Data." *JASA* 59(1964):402–420.

[26] Little, John D.C. "Aggregate Advertising Models: The State of the Art." *Operations Res.* 27(1979):629–667.

[27] Maddala, G.S. *Econometrics*. New York: McGraw-Hill Book Company, 1977.

[28] Mann, D.H. "Optimal Theoretic Advertising Stock Models: A Generalization Incorporating the Effects of Delayed Response from Promotional Expenditure." *Mngmnt. Science.* 21(1975):823–832.

[29] Nerlove, M. and F.V. Waugh. "Advertising Without Supply Control: Some Implications of a Study of the Advertising of Oranges." *J. Farm Econ.* 43(1961):813–837.

[30] Nerlove, Marc and K.J. Arrow. "Optimal Advertising Policy Under Dynamic Conditions." *Economica.* 29(1962):129–142.

[31] Rao, Potluri and R.L. Miller. *Applied Econometrics*. Belmont CA: Wadsworth Publishing Company, Inc., 1971.

[32] Simon, J.L. and J. Arndt. "The Shape of the Advertising Response Function." *J. Adv. Res.* 20(1981):11–28.

[33] Theil, Henri. *Principles of Econometrics*. New York: John Wiley & Sons, Inc., 1971.

[34] Thompson, S.R., D.A. Eiler, and O.D. Forker. "An Econometric Analysis of Sales Response to Generic Milk Advertising." *Search* 6(1976) Cornell University Agr. Exp. Sta. Bull. No. 3.

[35] Vidale, M.L. and H.B. Wolfe. "An Operations Research Study of Sales Response to Advertising." *Operations Res.* 5(1957):370–381.

[36] Waugh, Frederick V. "Needed Research on the Effectiveness of Farm Products Promotions." *J. Farm Econ.* 41(1959):364–377.

[37] Wildt, Albert D. "Estimating Models of Seasonal Market Response Using Dummy Variables." *J. Mkting. Res.* 14(1977):34–41.

[38] Wolffram, R. "Positivistic Measures of Aggregate Supply Elasticities: Some New Approaches - Some Critical Notes." *Amer. J. Agr. Econ.* 53(1971):356–359.

[39] Zielske, Hubert. "The Remembering and Forgetting of Advertising." *J. of Mkting.* 23(1959):239–243.