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Competitive advertising interference can occur when viewers of advertising for a focal brand are also exposed to advertising messages for competing brands within a short period (e.g., one week for television advertising). Although competitive advertising interference has been shown to reduce advertising recall and recognition and brand evaluation measures, no studies have examined its impact on brand sales. In this research, the authors use a market response model of sales for two grocery categories for a large grocery chain in the Chicago area to study the extent to which competitive advertising interference influences sales. The model enables the authors to capture the "pure" own-brand advertising elasticities that would arise if there were no competitive interference. The results show that competitive interference effects on sales are strong. When one or more competing brands advertise in the same week as the focal brand, the advertising elasticity diminishes for the focal brand. The decrease depends on the number of competing brands advertising in a particular week and their total advertising volume. The authors find that having one more competitor advertise is often more harmful to a focal brand's advertising effectiveness than if the current number of advertising brands increase their total advertising volume.

Keywords: advertising, competitive interference, aggregate scanner data, econometric models

The Effect of Competitive Advertising Interference on Sales for Packaged Goods

In 1997, television advertising expenditure in the United States was $42 billion. Only five years later, expenditure was more than $58 billion, a 38% increase, which is well above inflation levels during this period (www.adage.com). Increased spending on television advertising has resulted in a higher proportion of nonprogram material, now running at more than 16 minutes per hour in prime time (*Electronic Media* 2002). The number of nonprogram minutes in daytime television is even higher, at nearly 21 minutes per hour.

The downstream effect of increased advertising on television viewers is obvious; they are exposed to many more advertisements, which could potentially reduce advertising effectiveness. For example, recent industry evidence from Europe shows that advertising recall is lower in countries with higher levels of television advertising. Specifically, Byfield and Nazaroff (2003) report that in Denmark, where there are only 80 average television exposures per week per person, the Millward Brown awareness index is 150 (compared with the U.K. benchmark of 100).[1] However, in Italy, where there are 300 average exposures per week per person, the awareness index drops to only 50. Thus, an effect of increasing advertising levels is to decrease the recall of all advertisements. In addition, academic studies have found lower ad recall and recognition in the presence of too much advertising from competitors (Burke and Srull 1988; D'Souza and Rao 1995; Keller 1987, 1991). Increasing advertising content on television also increases ad avoidance behavior (Danaher 1995; Lafayette 2004), such as

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[1]The awareness index measures the percentage increase in survey-based advertising recall for a brand per gross rating points of (usually television) advertising broadcast by a brand (Brown 1985). An index for a country is an average across a range of comparable brands or product categories.

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channel switching or time-shift viewing with a personal video recorder (Green 2003).

A commonly used term to describe the presence of high levels of advertising is "clutter." For television, clutter is the combination of commercials and other nonprogram material, such as program promotions and public service announcements. The increase in clutter over the past 40 years is due to both an increase in nonprogram time and an increase in the number of 15-second commercials (Brown and Rothschild 1993; Kent 1995). The topic of increasing advertising clutter is one of the most publicized issues in the advertising trade literature and continues to be one of the greatest concerns facing the advertising industry (Chunovic 2003; Lafayette 2004).

Kent (1993) makes a distinction between competitive and noncompetitive clutter. Competitive clutter, which is also called "competitive interference" (Burke and Srull 1988; Kent and Allen 1994), is clutter that arises from advertisements delivered by competing brands (within a category) at or near the same time and place as those for a focal brand. Kent (1993, 1995) finds that competitive clutter has a more harmful effect on ad recall than noncompetitive clutter. In this study, we focus on competitive clutter.

Most previous research on brand advertising interference has been conducted in laboratory settings, in which participants are exposed only to commercials and no editorial material (Burke and Srull 1988; Keller 1991; Kent and Allen 1994), resulting in limited external validity. Other studies of this topic have used unfamiliar brands, which Kent and Allen (1994) show are more prone to interference effects. Finally, previous marketing studies have examined the effect of competitive interference on recall, recognition, or brand evaluations rather than the all-important effect on sales (East 2003, p. 19). The purpose of this study is to complement existing research by examining how competitive clutter affects sales. We do so in the context of packaged goods, using well-known brands within two grocery categories for one grocery chain in a major U.S. metropolitan market.

RELEVANT LITERATURE

The prevalence of competitive clutter in U.S. television is documented by Kent (1995), who reports that in daytime network television, approximately 31 advertisements are broadcast per hour. Furthermore, depending on the network, somewhere between 19% and 29% of advertisements have a competitive commercial (i.e., with in the same product category) aired within the same hour on the same channel. This rises to between 23% and 35% during prime time, though fewer advertisements are broadcast in this time zone. Thus, over a longer period, such as a week, many advertisements will be subjected to interference effects from their competitors.

The harmful effect of high competitive clutter on consumer advertising response has been known to marketers for some time (Bagozzi and Silk 1983; Bettman 1979). Although early experimental work by Webb (1979) demonstrates that increased clutter levels reduce brand name recall, Brown and Rothschild (1993) find no such reduction. The important distinction between these two studies and the work of Burke and Srull (1988), D'Souza and Rao (1995), and Keller (1987, 1991) is that Webb (1979) and Brown and Rothschild (1993) do not have any competitive advertising in their experiments. Thus, a key environmental factor on the effect of clutter is the presence of competitive advertising.

When explaining the reason for the drop in advertising effectiveness due to competitive interference, it is important to distinguish between the role of time and the role of interference due to additional learning. Temporal effects, such as advertising decay or wearout (Axelrod 1980), are often incorporated into advertising response models (e.g., Bass et al. 2007; Little 1979; Lodish 1971; Naik, Mantrala, and Sawyer 1998).[2] However, the passing of time is not the only reason for a decrease in advertising response. Early experiments in psychology that control for temporal effects suggest that much of the "forgetting" is due to additional learning rather than to the passage of time (McGeoch 1932).

Thus, information from advertising can be "unlearned" because of subsequent exposure to competing brands' messages. This is known as retroactive, rather than proactive, interference (Bagozzi and Silk 1983; Burke and Srull 1988). Burke and Srull (1988) find that aided recall for a focal brand's advertising is lower after exposure to advertising from competing brands. Keller (1987) finds that proactive competitive interference also inhibits ad and brand recall, but he could not demonstrate any impact of competitive interference on brand evaluations (i.e., ad and brand attitude and purchase intentions). However, a follow-up experiment by Keller (1991) demonstrates the detrimental effects of competitive interference on brand evaluations. His study also shows that interference effects are alleviated by using advertising retrieval cues in the form of executional information from the original advertisement.

In general, interference effects are perceived as deleterious to advertising effectiveness, but in a recent study, Jewell and Unnava (2003) exploited interference effects in the situation in which a brand is trying to promote a new or modified attribute. The competing advertisements help consumers "forget" the previously advertised attributes for the focal brand. In this unusual setting, advertising interference is rather helpful.

Previous research on competitive interference has several limitations, which we now detail. First, Burke and Srull (1988), Keller (1987, 1991), and Kent and Allen (1994) all use student samples or convenience samples for a near-forced-exposure situation in a laboratory setting. Second, these same studies expose participants only to commercials, without embedding them in a realistic media viewing environment with program or editorial material. Therefore, participants are likely to pay more attention to commercials when they have few or no environmental distractions or competing visual entertainment, such as a program. Third, previous experimental work has allowed either one or up to only three or four competitive advertisements per brand, whereas actual exposure levels in today's television envi-

[2]Bass and colleagues (2007) and Naik, Mantrala, and Sawyer (1998) distinguish between copy and repetition wearout, both of which are related to time. That is, the longer an ad campaign proceeds, the more likely copy and repetition wearout effects will arise. We do not have copy and repetition data for the advertisements in our empirical example, but we are able to test for any possible effect of time on advertising elasticity, as well as competitive interference effects. The outcome of these tests shows that time is not significantly related to advertising response, but interference effects remain significant.

ronment are typically much higher (Kent 1995). Fourth, Kent and Allen (1994) argue that a further external validity problem of Burke and Srull's (1988) and Keller's (1987, 1991) studies is their use of fictitious or unfamiliar brands. Kent and Allen (1993, 1994) find that competitive interference effects are not as marked for familiar brands. Fifth, all previous experimental studies have used print or radio (D'Souza and Rao 1995) rather than the television medium. Given that competitive clutter is commonly associated with television, it is apparent that work needs to be done on this high-spend medium. Finally, all previous studies have examined the effect of competitive interference on recall, recognition, or brand evaluations rather than on sales.[3] As a criterion for advertising effectiveness, sales is of much interest to advertisers (East 2003, p. 19).

Our study builds on previous research on competitive clutter effects by addressing the previously mentioned shortcomings. Specifically, we use actual weekly sales and spot television advertising data for the Chicago area in 1991. We examine multiple brands in two categories: liquid laundry detergent and raisin bran ready-to-eat (RTE) cereals. In addition, we use Nielsen television ratings data for this period to establish the weekly audience size (measured in gross rating points [GRPs]) for each brand that advertises. We demonstrate that competitive advertising reduces the own-brand advertising elasticity by approximately one-half. We further show that brand sales are affected by the number of competitors and the total volume at which they advertise.

The article proceeds as follows: First, we develop a robust and econometrically sound sales response model suitable for our weekly sales data. The model accommodates all the marketing-mix factors that potentially affect sales. Second, we construct a reasonable measure of competitive clutter that allows for the number of competing brands that advertise simultaneously and the volume of their advertising. Third, we fit the model to two grocery categories and test to determine whether competitive clutter influences advertising response. Fourth, we use the fitted model to observe the effect of competitive interference on brand sales. We conclude with some advice about how advertisers can reduce the effects of advertising interference on their brands.

THE MODEL

Model Relating Marketing Effort to Sales

The essence of our study is to look for possible competitive advertising interference effects on the sales of a focal brand. Therefore, an important starting point is to develop a demand model that relates a brand's sales to its own advertising and that of its competitors. However, we cannot ignore the potential effects of other marketing factors, such as price and promotion. Blattberg, Briesch, and Fox (1995) and Lambin (1976, p. 101) report that these variables have a stronger influence on sales than advertising. Thus, we require a complete demand model that relates all observed marketing variables to sales. Hanssens, Parsons, and Schultz (2001) and Leeflang and colleagues (2000) review the relevant marketing issues when constructing a model for weekly scanner data. Furthermore, Greene (2003) and Leeflang and colleagues (2000) highlight the pertinent econometric concerns. The upshot is that a robust model for market-level, weekly scanner data should be capable of handling the following issues:

1. Aggregation bias arising from combining data across stores within a market,
2. The influence of unobserved variables (i.e., misspecification bias),
3. Serial correlation in weekly sales for each brand,
4. Endogeneity effects between sales and advertising (i.e., simultaneity bias),
5. Carryover effects of advertising, and
6. Contemporaneous correlation in sales among all the brands within a category.

Issues 1, 2, 4, and 5 result in biased parameter estimates in a demand model, and Issues 3 and 6 result in inefficient estimators (Christen et al. 1997; Greene 2003). We now develop a demand model that systematically addresses each of the six issues and permits the inclusion of any number of marketing-mix variables.

Model Development

Our sales data come from more than 80 grocery stores in a large market, in which information is collected by in-store scanners. Such data are now routinely available and form the basis for decisions regarding in-store promotions, product assortment, and shelf allocation (Blattberg and Neslin 1990). Because we have sales data separately for each store, we could potentially use disaggregate store-level data, as Montgomery (1997) uses, for example. However, our advertising data are not at the store level. Rather, advertising is monitored only for the entire market. Given that the primary focus of our study is on the effects of advertising on sales, it seems appropriate to use sales data that are aggregated to the same market level as the advertising data. To address Issue 1—namely, aggregation bias—we use a result in the work of Christen and colleagues (1997), who show that there is no aggregation bias when sales and price data across stores are aggregated with the geometric mean and when a multiplicative model is used. A robust multiplicative model that incorporates all the marketing-mix variables and allows for own-brand and cross-brand effects is based on Christen and colleagues' (1997) model, which, for data aggregated across stores, is as follows:

$$(1) \qquad \mathrm{Sales}_{it} = \left[\prod_{j=1}^{B} (\mathrm{Price}_{jt})^{\beta_{ij}^{\mathrm{Price}}}\right]\left[\prod_{j=1}^{B} (\mathrm{Adv}_{jt})^{\beta_{ij}^{\mathrm{Adv}}}\right]\left[\prod_{k=1}^{K} (X_{ikt})^{\beta_{ik}}\right]\exp(u_{it}),$$

where Sales_{it} is the geometric mean of sales across all the stores in the market for brand i (i = 1, …, B) in week t (i.e.,

[3]A study by Metwally (1978) examined whether competing brands react to each other's television advertising with the aim of maintaining market share. His study is based on just the top two brands in each of six Australian packaged goods categories and uses annual market share, price, and advertising data for the period 1960–1976. He finds that in five of the six categories, competitive advertising reactions are present and tend to "self-cancel." That is, for his brands, advertising appears to be used mostly to maintain market share rather than to stimulate sales. Netter (1982) examines the possible influence of industry-level advertising on sales of durable and nondurable goods. However, his study uses just cross-sectional data, not time-series data, and does not explicitly capture competitive interference effects that might influence brand-level sales.

$\text{Sales}_{it} = [\prod_{l=1}^{L} \text{Sales}_{ilt}]^{1/L}$, where Sales_{ilt} is the quantity sales for brand i in store l); Price_{it} is the corresponding geometric mean of price across all stores; Adv_{it} is some measure of market-level advertising; $(X_{i1t}, \ldots, X_{iKt})$ are a set of K promotion covariates, such as the occurrence of feature and display activity; and u_{it} is a random disturbance term. By taking the log of both sides, we obtain the so-called log-log model, as follows:

$$(2)\quad \log(\text{Sales}_{it}) = \sum_{j=1}^{B} \beta_{ij}^{\text{Price}} \log(\text{Price}_{jt}) + \sum_{j=1}^{B} \beta_{ij}^{\text{Adv}} \log(\text{Adv}_{jt}) + \sum_{k=1}^{K} \beta_{ik} \log(X_{ikt}) + u_{it}.$$

Because of its flexibility, Christen and colleagues (1997) and Wittink and colleagues (1988) strongly endorse this model as a demand model for time-series sales data. There are several features of this model that deserve highlighting. First, the model allows for both own-brand and cross-brand effects for price and advertising. Many studies have shown the importance of cross-price effects (Leeflang et al. 2000), but only a few have examined cross-advertising effects (Clarke 1973; Kamen 1987; Lambin, Naert, and Bultez 1975). Possible cross-advertising effects are highly relevant in our application because competitive advertising might affect the focal brand's advertising either indirectly, by attenuating the impact of own-brand advertising, or directly, through a simple cross-brand effect. Cross-brand effects manifest in the β_{ij}^{Adv} coefficients ($j \neq i$). To clarify, a direct cross-brand effect of advertising involves customers being convinced by a competing brand's message that its brand is superior on a subset of attributes (e.g., taste, nutrition, price), whereas an indirect attenuation effect stems from competitor advertising diluting (e.g., through "unlearning") the advertising message from a focal brand. Note that cross-brand effects can occur even when the focal brand does not advertise, whereas interference effects can occur only when the focal brand advertises. Subsequently, we show how the indirect effects are captured. The second appealing feature of Equation 2 is that because it is a log-log model, own- and cross-elasticities are obtained directly from the regression coefficients $\beta_{ij}^{\text{Price}}$, β_{ij}^{Adv}, and β_{ik}. For example, β_{ii}^{Adv} corresponds to the own-brand advertising elasticity for brand i.[4]

Issue 2 pertains to the impact of omitting unobserved brand-specific effects from the model. For example, we do not have data on shelf-space allocation for each brand. When this is the case, Boulding (1990) recommends that brand-specific dummy variables be included in the model. In our case, we simply add the parameter α_i to Equation 2.

With respect to Issue 3, for time-series data on weekly sales, it is reasonable to expect serial correlation from one week to the next (Jacobson 1990), in which case the disturbance term in Equation 2 is better modeled by

$$(3)\quad u_{it} = \rho_i u_{it-1} + \varepsilon_{it},$$

where $|\rho_i| < 1$ and ε_{it} is an independent random disturbance, distributed normally with mean zero and constant variance. Note that we permit the autocorrelation parameter ρ_i to vary for each brand. Dealing with autocorrelation in this way has the added benefit of allowing for any remaining misspecification in the model that is not captured by the brand-specific dummy variables (Greene 2003, p. 250). This allowance for autocorrelation addresses Issue 3.

With respect to Issue 4, endogeneity in demand models for aggregate and panel data using grocery store scanner information has received renewed attention in the marketing literature (see Chintagunta 2001; Villas Boas and Winer 1999), even though endogeneity is an old problem in econometrics and was originally addressed in sales/advertising models by Bass (1969) and Bass and Parsons (1969). Little (1979, p. 659) and Leeflang and colleagues (2000, p. 382) argue that endogeneity is much less likely to arise for weekly scanner data because firms cannot react to their own sales and competitor advertising in such short periods. However, as we show subsequently, our advertising data come from spot television, in which advertisers have greater opportunity to adjust their advertising according to their own recent sales and advertising and that of their competitors.

We allow for possible endogeneity by using instrumental variables (Greene 2003). An added complication in our model is serially correlated errors, but Fair (1970) proposes a method for this situation that produces consistent parameter estimates. Fair's two-step procedure is to regress Adv_{it} on sales, advertising, promotion, and price for all brands and for periods t – 1 and t – 2. Predicted values $\hat{\text{Adv}}_{it}$ are obtained from these B regression models, and these become instrumental variables that are substituted for Adv_{it} in Equation 2. In the marketing literature, Jacobson (1990) successfully uses Fair's method for estimating simultaneous equations with serial correlation.

Returning to the original and complete model in Equation 2, we now have B sales equations. The equation for brand i is as follows:

$$(4)\quad \log(\text{Sales}_{it}) = \alpha_i + \sum_{j=1}^{B} \beta_{ij}^{\text{Price}} \log(\text{Price}_{jt}) + \sum_{j=1}^{B} \beta_{ij}^{\text{Adv}} \log(\hat{\text{Adv}}_{jt}) + \sum_{k=1}^{K} \beta_{ik} \log(X_{ikt}) + u_{it},$$

where $\hat{\text{Adv}}_{jt}$ is the advertising instrument for brand j at time t.[5]

Issue 5 is advertising carryover, in which advertising from previous periods might influence sales in the current period (Leone 1995). Hanssens, Parsons, and Schultz (2001, pp. 142–52) exhibit several methods for modeling advertising carryover. The method that is most compatible with the multiplicative model in Equation 2 is Broadbent's (1979) Adstock model. Adstock is essentially an exponential smoothing of the advertising measure. To be consistent with the log-log model in Equation 4, we need to smooth the advertising instruments exponentially, as follows:

[4]This model necessarily implies a diminishing-return shape for advertising response. Simon and Arndt (1980) show that diminishing returns are more prevalent than an S shape, especially for mature products, such as ours.

[5]In our application, the predicted values of the advertising instrument are always positive, so we had no problem with taking logs in the empirical analysis.

$$AS_{it} = \psi AS_{i,t-1} + (1-\psi)\hat{Adv}_{it}, \quad (5)$$

where AS_{it} is the Adstock for brand i at time t and ψ is a smoothing parameter bounded between 0 and 1.[6] It is not difficult to show that Equation 5 implies that

$$AS_{it} = (1-\psi)\sum_{k=1}^{t} \psi^{t-k}\hat{Adv}_{ik}, \quad (6)$$

which shows that Adstock is a geometrically weighted average of current and previous period advertising. We now replace $\hat{Adv}_{it}$ in Equation 4 with the Adstock variable in Equation 6 to incorporate possible advertising carryover effects. Leeflang and colleagues (2000, p. 89) show that allowing for carryover in this way changes the interpretation of the β_{ij}^{Adv} coefficients. Now, β_{ij}^{Adv} is the long-term advertising effect, and $(1-\psi)\beta_{ij}^{Adv}$ is the short-term effect. Thus, when we fit Equation 4 using the Adstock measure of Equation 6, the estimated coefficients are the long-term advertising elasticities.

Issue 6 suggests that it is necessary to allow for potential contemporaneous correlations among the brands within a category by permitting (ε_{1t}, ε_{2t}, …, ε_{Bt}) to have a general covariance structure (i.e., not necessarily diagonal). Therefore, we estimate the system of B equations in Equation 4 with the seemingly unrelated regression (SUR) method. This combination of instrumental variables followed by SUR estimation means that we are using three-stage least squares estimation, which typically results in lower standard errors for the parameter estimates than if SUR had not been used (Greene 2003, p. 407).

This completes the development of the six key components of our model. Now, we turn our attention to a model for own-advertising elasticities that has the ability to "tease out" the effects of competitive interference.

Clutter's Effect on Own-Advertising Elasticity

A competitor's advertising can affect a focal brand in at least two ways. The first is through a direct cross-brand effect. Clarke (1976) observes only negative cross-brand effects of competitor advertising, in which the advertising of a competing brand diminishes the sales of a focal brand; brands are considered in a pairwise way. In contrast, Lambin, Naert, and Bultez (1975) report both positive and negative cross-brand effects. The second, indirect way that a competitor's advertising might manifest is through attenuation of the focal brand's advertising elasticity due to competitive interference (Burke and Srull 1988; Keller 1987, 1991; Kent and Allen 1994). That is, a brand's advertising elasticity is lower than it would be if none of its competitors simultaneously advertise.

The sales model in Equation 4 gives us the flexibility to capture the effects of competitor advertising, both direct and indirect. Direct cross-brand effects are obtained from the regression coefficient β_{ij}^{Adv} when $j \neq i$, whereas indirect own-brand effects manifest in β_{ii}^{Adv}. However, an enhancement is required for β_{ii}^{Adv} because if competitive advertising interference attenuates the focal brand's elasticity, β_{ii}^{Adv} should be modeled as a function of competitive clutter. We expect attenuation to increase as the quantity of competitive clutter increases. Conversely, for low levels of competitive clutter, we expect little effect on the focal brand's advertising elasticity. Such a situation is consistent with an exponential decay model of the following form:

$$\beta_{ii}^{Adv} = \delta_i e^{\lambda C}, \quad (7)$$

where C denotes competitive clutter (we define this subsequently) and δ_i and λ are parameters to be estimated. If $\lambda < 0$, own-brand advertising elasticity decreases as competitive clutter increases. When there is no competitive clutter ($C = 0$), $\beta_{ii}^{Adv} = \delta_i$ so that δ_i is a measure of the "pure" advertising elasticity—that is, the advertising elasticity that would exist in the presence of no competitive clutter.

Note that we allow δ_i in Equation 7 to vary by brand, but λ is the same for each brand. This is because we conceptualize competitive interference as resulting from advertising across the entire category, not just from a specific brand. The direct effect of competitive advertising from a specific brand is already captured in our model by the cross-advertising effects, β_{ij}^{Adv}, $j \neq i$.

Another possible functional form for β_{ii}^{Adv} is a reverse S-shaped function, which can be modeled by a logistic function:

$$\beta_{ii}^{Adv} = \phi_i \frac{e^{\gamma_2(C-\gamma_1)}}{1+e^{\gamma_2(C-\gamma_1)}}, \quad (8)$$

where ϕ_i, γ_1, and γ_2 are parameters to be estimated. If competitive clutter effects attenuate advertising elasticity, then $\gamma_2 < 0$, in which case β_{ii}^{Adv} decreases to zero as C increases. The parameter γ_1 is a location parameter and determines the competitive clutter threshold at which attenuation effects become noticeable.

Operationalization of the Clutter Measure

Webb and Ray (1979) and Brown and Rothschild (1993) describe television clutter as the sum of all nonprogram material, such as commercials, television program promotions, and public service announcements. As mentioned previously, we focus only on competitive clutter, or interference (Burke and Srull 1988; Kent and Allen 1994). Television competitive clutter derives from commercials that are broadcast at the same or a similar time as a focal brand, either accidentally or deliberately, resulting in a possible dilution of the effectiveness of the focal brand's advertising.

We conceptualize competitive clutter as being a feature only of competitor advertising rather than focal-brand advertising. From a modeling point of view, it would also be problematic to have the focal brand's advertising included in the C term of Equation 7 because the focal brand's advertising would then be one of the independent variables in the model of Equation 4 and would also be present in the regression coefficient for that independent variable. Previous literature (Burke and Srull 1988; D'Souza and Rao 1995; Kent and Allen 1994) shows that competitive interference increases if the competitor brands advertise at higher levels concurrent with the focal brand. In addition, Anderson and colleagues (1998) and Keller (1987, 1991) show that interference effects are stronger when more brands advertise simultaneously; that is, recall declines as the number of competitors increases. Thus,

[6]We also allow for the possibility of the smoothing parameter varying by brand (i.e., ψ_i), but we find for our two categories that the ψ_i parameters are close in magnitude, and varying by brand makes little material difference to the downstream advertising elasticity estimates.

competitive clutter can be viewed as a combination of the proportion of competitor brands advertising in the category and the total amount of advertising these brands deliver. We denote C_{it} as the competitive clutter broadcast against brand i at time t and A_{it} as a measure of advertising volume for brand i in week t. Our measure for advertising volume is GRPs, which are the sum of ratings achieved across all the advertising spots (i.e., sometimes referred to as "advertising weight"). Gross rating points are the buying and selling currency of television advertising (Sissors and Baron 2002). We then define competitive clutter as

$$C_{it} = \left(\frac{\sum_{j \neq i} I_{\{A_{jt}\}}}{B - 1}\right) \sum_{j \neq i} A_{jt}, \tag{9}$$

where $I_{\{A_{jt}\}} = 1$ if $A_{jt} > 0$—that is, if brand j advertises in week t—and 0 if otherwise. Thus, C_{it} is the product of the proportion of competing brands that are advertising and the total advertising volume of these competing brands. We substitute C_{it} for C in Equations 7 and 8 at the estimation stage. Competitive interference effects will be greatest when a large proportion of competitor brands advertise at heavy levels at the same time the focal brand is advertising. Subsequently, we show that a model with both the proportion component of Equation 9 and the total advertising volume component gives an improved fit compared with a model that contains either one of the two components.

SOURCES OF DATA

To fit the model in Equation 4, we need weekly sales data for each brand, along with the corresponding weekly marketing-mix information, such as price, in-store promotion, and television advertising. Our approach to matching advertising to downstream sales data is to capture the aggregate weekly store sales across a region for each brand and simultaneously monitor the spot television advertising for the same geographic region. Television viewers in the region are potentially exposed to a brand's advertising (when it occurs), and this potentially stimulates sales in the grocery stores in the defined region. We first describe the source of our sales, price, and in-store promotion data and then describe the television advertising data, followed by the television ratings data.

Sales Data

Our sales data come from the well-known Chicago supermarket chain, Dominick's Finer Foods (DFF), which has 86 stores spread throughout the Chicago metropolitan area, accounting for approximately 20% of the region's grocery market. Hoch and colleagues (1995) provide a map of the distribution of DFF stores, which shows that they are spread over the length and breadth of Chicago, with concentrations in the more densely populated areas. Thus, it is reasonable to assume that sales from DFF stores are geographically representative of grocery stores for the Chicago metropolitan area, but our sales data are restricted to this one chain. Although our grocery sales are limited to just the DFF chain, there is no reason to believe that advertising attenuation effects are not present for other grocery chains in Chicago.

We examine two categories in detail: liquid laundry detergent and raisin bran cereals. Kent (1995) identifies RTE cereals and household products (e.g., laundry detergent) as being among the top ten categories with the highest levels of competitive interference. Our data cover the entire 52 weeks of 1991. The laundry detergent category has six brands, and raisin bran has three brands (see Table 1, Panels A and B, respectively). To accommodate different package sizes, the detergent sales data are based on volume sold; a standard size is Information Resources Inc.'s (IRI's) "equivalent unit" of 16 fluid ounces. For the raisin bran category, IRI's equivalent unit is a weight of 16 ounces. The market share for the detergent brands in Table 1, Panel A, is based on volume sales in fluid ounces; Tide is the dominant brand in the category. As might be expected, Kellogg products dominate the cereal category.

Table 1

DESCRIPTIVE STATISTICS

A: Liquid Laundry Detergent Category

Brand	*Market Share (%)*	*Average Price (¢)*	*Average Bonus (%)*	*Average Price-Off (%)*	*Weeks of Advertising*	*Average Spots per Week*	*Average GRPs per Week*	*Average C_{it}*
All	13.7	71.1	15.0	1.0	21	3.5	25	151.3
Cheer	10.0	102.4	14.7	2.1	17	2.5	10	155.9
Era	7.3	102.5	19.3	.0	47	16.6	64	103.5
Solo	12.0	84.2	15.4	2.3	39	15.0	59	108.9
Surf	11.2	93.0	8.2	.2	30	5.3	35	136.3
Tide	45.9	99.2	28.5	1.8	24	11.3	48	126.4
All brands	100.0	93.4	16.9	1.2	30	9.0	40	130.4

B: Raisin Bran Cereal Category

Manufacturer	*Market Share (%)*	*Average Price ($)*	*Average Bonus (%)*	*Average Price-Off (%)*	*Weeks of Advertising*	*Average Spots per Week*	*Average GRPs per Week*	*Average C_{it}*
Kellogg	63.9	2.41	2.7	.5	36	8.2	32.5	43.0
Post	18.8	2.40	5.9	.0	42	7.3	23.3	47.4
General Mills	17.3	3.16	.0	.0	38	8.8	24.0	46.5
All brands	100.0	2.5	2.9	.2	38.7	8.1	26.6	45.6

The average price for detergent is also based on IRI's equivalent unit of 16 fluid ounces. Thus, for example, the average price of 64 fluid ounces of Tide is $\$.992 \times 4 = \$3.97$. We also include measures of each brand's in-store promotional activities (bonus and price-off). An example of a bonus is a "buy-one-get-some-free" deal. Each Universal Product Code (UPC) is coded as 1 or 0 to indicate the presence or absence of a promotion. Each UPC also has a weight assigned to it that represents the share of the total volume sold of the brand across the entire 52 weeks of our observation period, which is consistent with the aggregation method that Little (1998, p. 479) recommends. The price-off promotion variable uses the same construction as bonus but indicates the presence or absence of a straightforward price discount. Finally, we considered including distribution variables, but distribution for these brands is almost always 100%, and there is too little variation across either time or brands to allow distribution to be used as a control variable.

Advertising Data

Advertising for national brands, such as those in Table 1, can potentially be in media such as radio, magazines, newspapers, and television.[7] Given that competitive clutter is viewed as a concern primarily for television, it is natural to focus attention on just this medium. In the case of laundry detergent and RTE cereals, there are some additional reasons for considering just television. The Leading National Advertisers (LNA; 1992) report for 1991 shows that in the liquid laundry detergent category, Procter & Gamble and Unilever allocated 86% and 76%, respectively, of their total advertising budget to just television.[8] Of the brands in Table 1, Panel A, only Tide has any significant nontelevision advertising expenditure. For the RTE cereals category, the average proportion of advertising budget allocated to television for the five manufacturers in Table 1, Panel B, is 83%. This is particularly true for General Mills and Kellogg, both of whose television allocation exceeds 95% of their combined advertising budget. Therefore, it is reasonable to use advertising data only for television because it is the dominant medium for our product categories.

Our television advertising data come from Arbitron's spot television commercial monitoring service, the Broadcast Advertising Reports, for the same year as our sales data, namely, 1991. This service monitors the main commercial television stations continually, logging all advertisements and programs. Data are recorded on the time and day that each program and advertisement are broadcast on each station, as well as the length of each commercial. For the Chicago metropolitan area, the Arbitron service monitors seven television stations, including affiliates of all four major networks.

Note that Arbitron monitors just spot television and not network, syndicated, and cable television. This is not a severe limitation, as revealed by the LNA (1992) report, which separates out television advertising expenditure by television platform for each manufacturer. For example, it reports that Procter & Gamble and Unilever allocate 28% and 30%, respectively, of their television spend to spot television. Data from the 1991 LNA report show that the correlation between spot television ad expenditure and total television ad expenditure for the manufacturers of our detergent and cereal brands is .93. Thus, spot television information is a good proxy for total television commercial activity.[9] A further advantage of using just spot television is that it has much shorter purchasing lead times (two weeks to two months) than network television advertising, which is typically bought 3–12 months in advance (Sissors and Baron 2002). Thus, spot television is more suitable for tactical competitive advertising, which is an area of interest in this study.

Television Ratings Data

At this stage, our advertising data comprise the time and day of each spot broadcast by each brand. Not all spots carry the same weight in terms of audience size (Dubé, Hitsch, and Manchanda 2005). For example, a late-night spot will not have the same audience size as one aired during prime time. We account for the differing impact of spots by obtaining the rating for each spot. The sum of these ratings constitutes GRPs (Katz 2003; Sissors and Baron 2002).

The ratings data from Nielsen Media Research are based on a sample of approximately 2000 households in the Chicago Designated Market Area. Approximately 375 households complete a quarter-hour television diary for a one-week period over a four-week period, for a total of 1500 diary households. An additional 500 households have "peoplemeters" installed for continuous measurement. Data are averaged across four weeks corresponding to quarterly "sweeps" in February, May, August, and November, with a new set of 1500 diary homes recruited for each quarter. The February sweep is intended to cover programs shown in January, February, and March; the May sweep covers programs shown in April, May, and June; and so on. Although diary-based ratings are collected only in February of the first quarter, because of the regularity of programming in January through March, it is reasonable to assume that ratings for the month of February are indicative for the entire quarter. The same is also true of the other quarters. The ad spots vary week by week, but the ratings attached to each spot are constant for each quarter, in accordance with the Nielsen sweeps. Near-constant ratings over a quarterly period are the norm even when daily peoplemeter ratings are available (see Barwise and Ehrenberg 1988), so using quarterly sweeps is not considered a restriction.

[7]There might also be DFF feature advertising in local areas, but this would normally coincide with in-store promotions and would cover many more than just two categories.

[8]Unilever manufactures the brands All and Surf, and Procter & Gamble manufactures the other four detergent brands in Table 1, Panel A.

[9]Because spot television represents approximately one-third of total television spending for detergent and cereal manufacturers, we could simply adjust the levels of spot television advertising spending for each manufacturer according to the proportion of their total spending allocated to spot television. This would entail dividing the Unilever spot television spending by .33 to obtain a reasonable estimate of its total television advertising levels. For the exponential model in Equation 7, if we divide C by an appropriate spot television adjustment, such as .33, then $\beta_{ii}^{Adv} = \delta_i \exp(\lambda C/.33) = \delta_i \exp(\lambda' C)$, where $\lambda' = \lambda/.33$. Thus, adjusting for the difference between spot television and total television ratings involves only a simple reparameterization. The logistic model of Equation 8 also accommodates a simple reparameterization. We do not actually make this adjustment, but it can be done if required.

The ratings metric we use is the proportion of households that watch a program. An advertisement that airs during a program is assigned the rating of that program. Because the quarterly sweeps do not necessarily cover the month for which we have advertising data (e.g., our February ratings data do not report ratings for a movie shown in January), the data may not reflect the actual rating for the program. In such cases, we use the average rating for the time slot during which the program is shown. In other cases, the programming may have changed from the month in which the sweep was performed. In such cases, we also take the typical ratings for that quarter. Only 250 (8%) advertising spot ratings are estimated in this way. In cases in which an advertisement is placed in a "break" between programs, we use the average rating of the programs surrounding the break.

Figure 1 illustrates sales, own-brand, and competitive clutter for Era in the detergent category. There is high variability in own-brand and competitor advertising. Several spikes in the sales data coincide with price promotions. Advertising effects are more subtle, but we note Weeks 26–29, during which Era's own advertising increases substantially from zero. During this four-week period, the price for Era is about constant. Competitive clutter in Weeks 27–29 is low, and during this time, sales for Era increase. However, they drop back to normal levels after competitive clutter overtakes own-brand advertising in Weeks 30 and beyond.

RESULTS

Model Comparison

We compare several models, ranging from a benchmark model with fixed own- and cross-brand advertising elasticities to models that accommodate various forms of competitive interference. All the models are fit using the SAS Model procedure (SAS 2004). This is an extremely versatile algorithm for fitting time-series data with linear and nonlinear models. Estimation with SUR results in a solution with the minimum weighted residual sum of squares. The first stage of model fitting requires the determination of the exponential smoothing parameter ψ in Equation 5. We achieve this using the model in Equation 4 but not incorporating the models for advertising elasticities in Equations 7 and 8. This avoids any possible confounding of interference and carryover effects. We use a simple grid search, varying ψ upward from 0 in increments of .01, looking for the value of ψ that results in the smallest sum of squared residuals. For liquid laundry detergent, $\psi = .21$, and for raisin bran cereals, $\psi = .16$. These relatively low values indicate that carryover effects are present but are not large (Broadbent 1979; Dubé, Hitsch, and Manchanda 2005).

As some of the models are nonlinear and not nested, we compare the models on the basis of the mean absolute difference (MAD) and mean square error (MSE) between actual and predicted log-sales.[10] These are averaged across all the brands in the category for a calibration period of 45 weeks and a validation period of 7 weeks. We also tried validation periods of 5 and 3 weeks, but there was no difference in the relative performance of the models. Table 2 provides the MSE and MAD values for the benchmark model and the two models that incorporate competitive clutter, as given in Equations 7 and 8. It shows that the exponential and logistic models perform the best for both the calibration and validation data and for all categories. Therefore, the need to allow for some form of attenuation in the own-brand elasticity through an exponential or logistic model is justified. Although there is little difference between the exponential and logistic models, the appeal of the exponential model is parsimony. With just one extra

[10]Comparison of the models based on log-likelihoods is not possible in our case. Gallant (1987, p. 139) shows that such comparisons are inappropriate for nonlinear models with serially correlated errors.

Figure 1

SALES, OWN ADVERTISING, AND COMPETITIVE CLUTTER FOR ERA

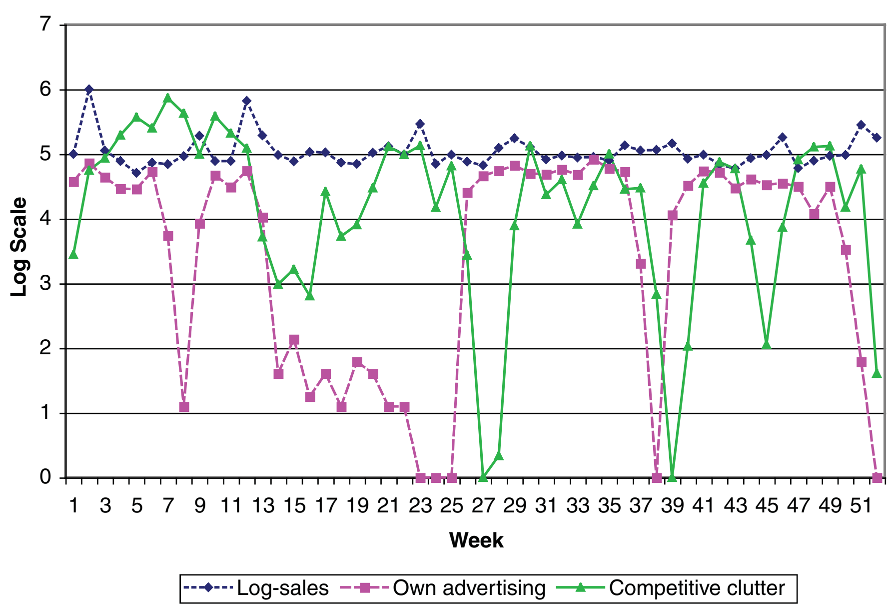


Table 2
MODEL COMPARISON

		Fixed Own-Brand Elasticity	Own-Brand Advertising Elasticity Incorporating Competitive Clutter	
			Exponential Model	*Logistic Model*
Detergents	Parameters	103	104	105
Calibration data: 45 weeks	MSE	.056	.055	.055
	MAD	.162	.161	.161
Validation data: 7 weeks	MSE	.185	.162	.164
	MAD	.353	.318	.321
Cereals: Raisin Bran	Parameters	34	35	36
Calibration data: 45 weeks	MSE	.027	.024	.023
	MAD	.122	.117	.115
Validation data: 7 weeks	MSE	.339	.301	.302
	MAD	.493	.461	.463

parameter, it has the smallest validation prediction errors for all the comparisons.

We also fit the models using two alternative definitions of competitive clutter—namely, the proportion of competitor brands advertising and the total competitor GRPs—which are the two respective components of Equation 9. Because these models use different data, they are not nested within the model using Equation 7 as the definition of competitive clutter, so again we compare performance using the validation period of the last 7 weeks. For detergents, there are sharp increases in MSE and MAD (8%–14%) in the validation period when we use just one of the two components of Equation 9. For raisin bran cereals, there are small decreases in MSE and MAD (2%–4%) when we use only competitor GRPs. The reason the largest change is observed for detergents is likely due to this category having the largest number of brands, and therefore there is more variability in the proportion of brands advertising each week. For the cereal category, each brand advertises frequently, so the proportion of competing brands is often one. Therefore, we conclude that it is best to combine the proportion of competing brands and the total competing advertising volume, as in Equation 9.

Parameter Estimates

Because there are so many cross-brand parameters for price and advertising, along with own-brand parameters for bonus and price-off, we report just the significant advertising parameters in Tables 3 and 4, respectively, for the laundry detergent and the raisin bran categories.[11] Both tables give parameter estimates for the benchmark model, which ignores interference effects, plus the two models that allow for such effects.

We are interested primarily in the parameters associated with competitive clutter, as given in Equations 7 and 8. In each of these two models, the parameters used to capture the effects of competitive clutter—namely, λ and γ_2—are negative and statistically significant. This shows that own-brand advertising elasticity decreases as competitive clutter increases. When we focus on the exponential model for the laundry detergent category, the estimate of δ_1 for Brand 1 (All) is .16. This might be termed the "pure" advertising elasticity because it is the elasticity when there is no competitive interference.[12] Contrast this with the lower estimate of .076, based on the benchmark model that ignores competitive interference. The same pattern occurs for Brands 2–4, for which the own-brand advertising elasticities for the model, assuming fixed elasticities, are somewhat smaller than the $\hat{\delta}_i$ values. The β_{ii}^{Adv} estimates are about half those of δ_i. For the raisin bran category, none of the own-brand advertising elasticities are significant for the benchmark multiplicative model, but two of the brands exhibit significant pure advertising elasticities under the exponential and logistic models. In other words, employing a commonly used and robust econometric model to uncover advertising effects for raisin brand cereals results in the conclusion that advertising is ineffective for all brands. However, when the model is modified to allow for competitive interference, advertising effects are present but do not manifest because of the high level of competitor advertising.

We now consider advertising cross-elasticities. In our model of Equation 4, advertising cross-brand effects are captured with a direct (pairwise) effect of a competing brand on a focal brand and with an indirect effect of all the competing brands on the own-brand elasticity for the focal brand. Tables 3 and 4 show that the estimated direct cross-elasticities can be either negative or positive. A pattern that emerges is that when a cross-elasticity involves a large brand advertising against a smaller focal brand, the cross-advertising elasticity is negative. Evidence of this can be observed in Table 3 when Tide advertises against Era ($\beta_{36}^{Adv} < 0$) and Solo ($\beta_{46}^{Adv} < 0$). In Table 4, when Kellogg's Raisin Bran advertises against General Mills Total, $\beta_{31}^{Adv} < 0$. In other instances, sales of big brands are assisted by the advertising of smaller brands, as $\beta_{43}^{Adv} > 0$ for Solo illustrates in Table 3 and $\beta_{12}^{Adv} > 0$ illustrates for Kellogg's Raisin Bran in Table 4.

Clutter's Effect on Own-Brand Advertising Elasticity

Figure 2 shows the effect of increasing competitive clutter on the advertising elasticity of Cheer in the laundry detergent category. The exponential model shows a steady

[11]We can report that all the significant own-price elasticities are large and negative, whereas those for bonus and price-off are positive but much smaller in magnitude. The complete set of estimates is available on request.

[12]Recall that because of our use of Adstock to handle advertising carryover, this is the long-term ad elasticity.

Table 3

PARAMETER ESTIMATES FOR THE SALES RESPONSE MODEL FOR LAUNDRY DETERGENTS

Cross-Elasticity Parameter[a]	*Fixed Model*	*Exponential Model*	*Logistic Model*
β_{32}^{Adv}	.075** (.028)	.066** (.027)	.061** (.027)
β_{36}^{Adv}	–.063** (.024)	–.046* (.025)	–.042* (.025)
β_{43}^{Adv}	n.s.	.039** (.016)	.039** (.015)
β_{45}^{Adv}	–.020* (.010)	–.015* (.009)	–.016* (.009)
β_{46}^{Adv}	–.063*** (.019)	–.055*** (.017)	–.054*** (.017)
β_{51}^{Adv}	.068* (.039)	.072* (.039)	.075* (.038)
	Own-Elasticities Parameter		
Brand	*Fixed Model:* β_{ii}^{Adv}	*Exponential Model:* δ_i	*Logistic Model:* φ_i
1. All	.076** (.034)	.160*** (.058)	.166*** (.059)
2. Cheer	.080*** (.029)	.179*** (.057)	.183*** (.055)
3. Era	n.s.	.058* (.033)	.066* (.036)
4. Solo	.032** (.013)	.055*** (.019)	.064*** (.020)
5. Surf	n.s.	n.s.	n.s.
6. Tide	n.s.	n.s.	n.s.
Interference Parameters			
λ	—	–.0063** (.0023)	—
γ_1	—	—	108.9** (46.6)
γ_2	—	—	–.0152** (.0066)

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.
[a]We denote the cross-elasticity between brands i and j as β_{ij}^{Adv}, where Brands 1–6 are, respectively, All, Cheer, Era, Solo, Surf, and Tide.
Notes: Standard errors are in parentheses. n.s. = not significant.

Table 4

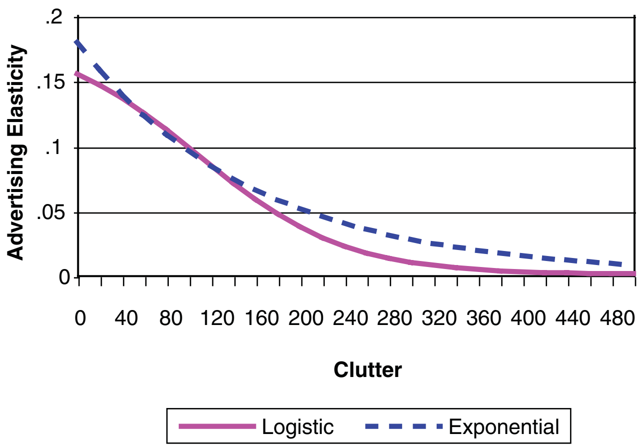
PARAMETER ESTIMATES FOR THE SALES RESPONSE MODEL FOR RAISIN BRAN CEREALS

Cross-Elasticity Parameter[a]	*Fixed Model*	*Exponential Model*	*Logistic Model*
β_{12}^{Adv}	n.s.	.043* (.024)	.041* (.024)
β_{31}^{Adv}	–.025* (.013)	–.029* (.016)	–.027* (.016)
	Own-Elasticities Parameter		
Brand	*Fixed Model:* β_{ii}^{Adv}	*Exponential Model:* δ_i	*Logistic Model:* φ_i
1. Kellogg's	n.s.	.053* (.028)	.067* (.039)
2. Post	n.s.	.149*** (.033)	.168*** (.052)
3. General Mills Total	n.s.	n.s.	n.s.
Interference Parameters			
λ	—	–.029** (.014)	—
γ_1	—	—	n.s.
γ_2	—	—	–.052* (.027)

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.
[a]We denote the cross-elasticity between brands i and j as β_{ij}^{Adv}, where Brands 1–3 are, respectively, Kellogg's, Post, and General Mills Total.
Notes: Standard errors are in parentheses. n.s. = not significant.

decline in advertising elasticity as competitive clutter increases. For the logistic model, beyond a competitive clutter level of approximately 70, the advertising elasticity begins to fall quickly. The median competitive clutter level for Cheer is 151.7, its standard deviation is 93, and its range is 344. At the median level of clutter for Cheer, Figure 2 provides an estimated advertising elasticity of .068. However, when there is no competitive clutter, the exponential model advertising elasticity is nearly three times higher, at .179, showing the deleterious effects of competitive interference. To underscore this attenuating effect of competitive clutter, Table 3 shows that the estimated advertising elasticity for Cheer, using the benchmark fixed-elasticity model, is .080. First, note that this is close to the .068 value that the exponential model predicted. Second, note that this means that if competitive clutter effects are ignored and the advertising elasticity is naively estimated with a robust log-log multiplicative model, we will obtain a value of .08, which is relatively low (Assmus, Farley, and Lehmann 1984; Leone and Schultz 1980). However, the advertising elastic-

Figure 2
ADVERTISING ELASTICITY FOR INCREASING CLUTTER: CHEER DETERGENT



ity estimate without clutter is .179. Competitive clutter masks the true effect of advertising on sales. We predicted the own-brand elasticities at the median competitive clutter levels for all the brands in Tables 3 and 4 and found that the exponential model consistently produces closer estimates to the benchmark model than the logistic model.

ADVERTISING AND CLUTTER EFFECTS ON SALES

We showed how increasing competitive clutter levels reduces advertising elasticity. In this section, we focus on just advertising's effect on sales and assume that the other marketing-mix factors are held constant. We can obtain the expected value of sales for brand i from Equation 1 using the bias correction that Hanssens, Parsons, and Schultz (2001, p. 395) suggest, as follows:

$$E[Sales_i] = \left[\prod_{j=1}^{B}(Price_j)^{\beta_{ij}^{Price}}\right]\left[\prod_{j=1}^{B}(Adv_j)^{\beta_{ij}^{Adv}}\right]$$

$$\left[\prod_{k=1}^{K}(X_i)^{\beta_{ik}}\right]\exp(\sigma^2/2).$$

By setting price, price-off, bonus, and advertising at their average values, we obtain baseline sales. The expected sales lift for brand i relative to its baseline is as follows:

$$\text{(10)}\quad E[Sales_i]/(baseline\_sales) = (Adv_i/\overline{Adv_i})^{\delta_i \exp(\lambda C_i)}.$$

Equation 10 shows that when C_i is held constant, increasing Adv_i for the focal brand increases its relative sales. However, the amount by which its sales increases depends on competitive clutter, with high levels resulting in lower sales lift. To illustrate the effect of clutter on sales, we calculate the relative sales for All in the laundry detergent category, when this brand advertises at 50 GRPs. Figure 3 uses Equation 10 to plot the relative change in sales when two through all six brands in the category are advertising. By two brands advertising, we mean All and one other, and so on.

Note that as the number of GRPs for the other brands increases, the sales response to advertising for the focal brand declines. For just one other brand advertising, the decline in sales lift is not substantial, but it does become dramatic as the proportion of brands advertising in the category increases. Only when the competitor brands advertise at low levels can All expect to obtain a substantial response to its advertising. For example, when the five other brands in Figure 3 broadcast 150 total GRPs and All advertises 50 GRPs (twice its weekly average), long-term sales for All increase by 4.4%. However, when the other five brands have a lower total of 50 GRPs, matching All's 50 GRPs, the long-term sales lift for the focal brand nearly doubles to 8.4%. The corresponding values for the short-term gains are 3.5% and 6.7%, respectively.

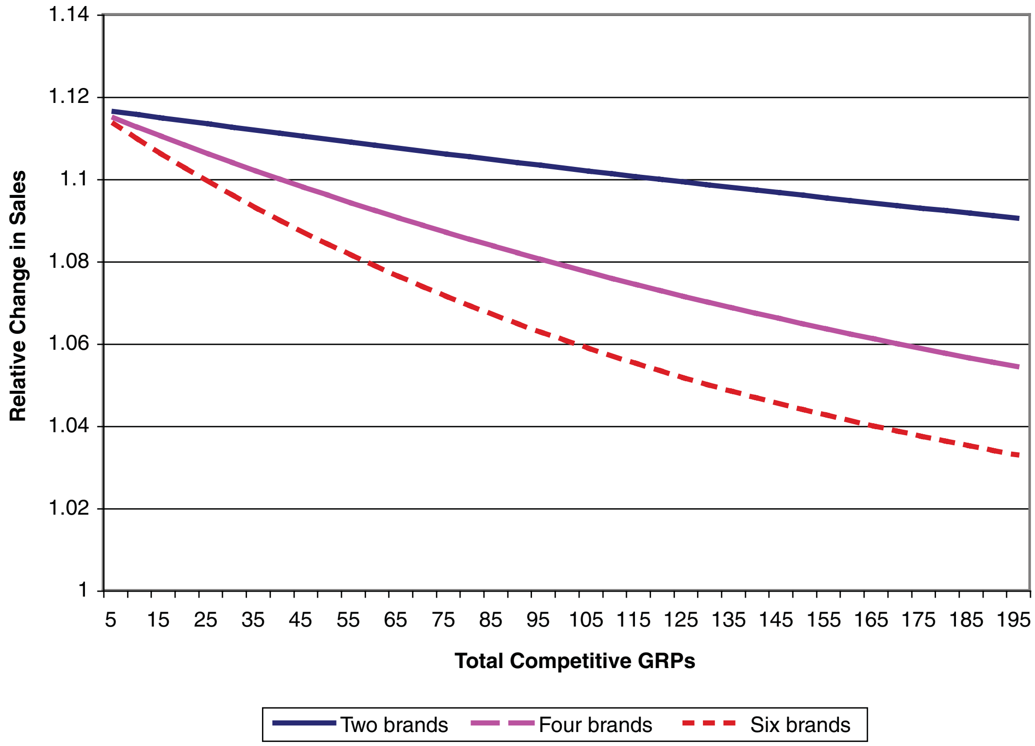
Figure 3 also illustrates that competitive interference effects are heavily affected by the proportion of brands simultaneously advertising. For example, the long-term sales increase when All advertises at 50 GRPs and five competing brands advertise at 30 GRPs each is 4.4%. However, when All's advertising level is 50 GRPs but only three competing brands advertise at 50 GRPs each, the long-term sales increase for All rises to 6.5%. That is, although in both cases the total competitive GRPs are 150, greater sales gains due to focal-brand advertising can be expected when fewer competitors advertise in the same week.

The results lead to the question, Is it better to aim for matched advertising levels with competing brands or attempt to attain exclusive advertising? Suppose that there are three detergent brands with identical annual advertising budgets. To make predictions of such hypothetical advertising strategies, we use the advertising elasticity information for All, as in Figure 3, and assume that the other two brands have the same advertising elasticity and category clutter effect, as in Table 3. In the first hypothetical scenario, all three brands advertise at 50 GRPs per week for three weeks. Our model predicts that the average weekly lift in sales will be 6.1%. In another hypothetical scenario, each brand advertises exclusively, in rotation, only Brand 1 in Week 1, only Brand 2 in Week 2, and only Brand 3 in Week 3. When a brand advertises exclusively, it spends three weeks of its usual advertising all in one week, amounting to 150 GRPs, followed by zero spending in the subsequent two weeks. Under this scenario, our model predicts a sales lift of 33% in the week the brand advertises. Averaging this over three weeks gives an approximate weekly average of 33/3 = 11%, almost twice the sales lift attained under an advertising matching strategy. It would be difficult to achieve exclusive advertising, but this example illustrates that advertisers should modify their media planning to gain the advantages of exclusive advertising.

SUMMARY AND CONCLUSION

Previous experimental research has found that competitive advertising interference lowers ad recall, brand attitude, and purchase intentions. Although these findings are robust in a controlled experimental setting, it is uncertain as to whether the findings generalize to a more real-world setting. In particular, does competitive advertising interference affect the sales of a focal brand? Aaker and Carmen (1982), Assmus, Farley, and Lehman (1984), and Lambin (1976) suggest such effects, but empirical evidence has been lack-

Figure 3
RELATIVE CHANGE IN SALES AS NUMBER OF BRANDS INCREASES WHEN ALL ADVERTISES AT 50 GRPS



ing. Our study addresses this shortcoming, with findings that are consistent with previous laboratory studies, by showing that sales are also negatively affected by competitive advertising interference. Although advertisers have probably suspected that high levels of competitive interference reduce the effect of advertising on sales, until now, the magnitude of the reduction has not been quantified. Our findings make a contribution in three areas: methodological, substantive, and advertising practice.

Methodological Findings

The starting point for our study is the development of an econometrically robust log-log model that is tailored to weekly scanner data aggregated across a market. The model enables us to estimate advertising elasticities from the model parameters (Leeflang et al. 2000). We enhance this model so that own-brand advertising elasticity can be decomposed into a pure advertising elasticity (when there is no competitive advertising) multiplied by either an exponential or a logistic function that, in turn, is a function of competitive advertising. This permits competitive advertising to manifest in two ways, either directly through cross-brand elasticities or indirectly through an attenuation of the own-brand elasticity.

We find that the inclusion of either the exponential or the logistic models of own-brand elasticities results in improved model fit compared with a benchmark log-log model. Because of its parsimony, its accuracy at predicting observed advertising elasticities in the presence of competitive clutter, and its better predictive performance for a validation period, the exponential model of elasticity attenuation is preferred over the logistic model. Another appealing feature of the exponential model is that the pure own-brand advertising elasticity is obtained directly from one parameter estimate when competitive clutter is zero.

An additional methodological contribution is the ascertaining of how competitive clutter should be measured. Previous experimental research has shown that both the number of brands and the amount of competitive advertising can potentially have an impact (Burke and Srull 1988; Keller 1991). We find that operationalizing competitive advertising interference as the interaction of the proportion of competing brands advertising in a week with the total volume of their advertising is better (in terms of model fit) than when either of these two components are used uniquely. This is particularly true for categories with a medium to large number of brands.

When developing our model, we listed six issues that should be addressed: aggregation bias, misspecification bias, serial correlation, endogeneity of advertising with sales, advertising carryover, and contemporaneous correlation. Our findings are most sensitive to misspecification bias, serial correlation, and contemporaneous correlation and least sensitive to the other three issues. Endogeneity is likely to be less important in our application because of the use of weekly rather than annual data. Although our model captures advertising carryover, a more critical issue is modeling serial correlation and unobserved brand-level effects with an autoregressive error structure and the use of brand-level intercepts.

Substantive Findings

For the two packaged goods categories studied, we found that competitive advertising interference results in (1) attenuation in own-brand advertising elasticities, with elasticities in a cluttered environment being about half those observed when no competitors are advertising, and (2) a decline in sales as the proportion of competing brands that advertise increases (even for the same total quantity of competitive advertising). Moreover, having one more competitor advertise is typically more harmful to a focal brand's advertising effectiveness than if the current advertising brands increase their total ad volume.

Advertising Practice Findings

In recent times, advertising spending has been increasingly questioned because of the difficulty of measuring its effectiveness and return on investment (Srivastava and Reibstein 2005). Although our findings on attenuated advertising response in the presence of competitive interference are sobering for advertisers, they also leave room for optimism. Our results show that advertising may be more effective than is currently believed because of the use of models that ignore competitive interference effects. We now know that sales response to advertising could be substantially higher if there is less competitive interference within a category. We observe the true potential (pure) effect of advertising on sales only when we account for competitive interference. Advertising could be even more influential if it is viewed in isolation of competitors' advertising. Previous meta-analyses of advertising elasticities by Leone and Schultz (1980) and Assmus, Farley, and Lehmann (1984), together with extensive field experiments by Lodish and colleagues (1995), have reported small (averages of .05–.22) or nonsignificant elasticities. Because none of these studies allow for possible interference effects, it is likely that they understate the effectiveness of advertising. The competitive media environment also needs to be taken into account. This somewhat deflects attention away from the creative part of the advertising process and puts the spotlight on ad budgeting, scheduling, and the overall media plan. Advertisers should be heartened to learn that their advertising creative and message may still be effective, but the deployment of advertising requires sharpening.

Regarding advertising budgeting, experienced advertisers in mature markets—of which Procter & Gamble, Unilever, Kellogg, and General Mills are good examples—often set advertising budgets in proportion to a brand's market share as part of a share maintenance strategy (Schroer 1990). Indeed, a plot of share of market (SOM) against share of voice (SOV) for the brands in our categories shows strong evidence of advertising budgets set to the SOV = SOM rule of thumb. Persistent use of the SOV = SOM strategy over the past 40 years has meant that as one brand increases its SOV to gain market share, its competitors have correspondingly increased their ad spending to maintain SOV and, therefore, market share. This has resulted in an escalation of ad spending (Metwally 1978; Schroer 1990), thus increasing demand for advertising. The combination of higher demand with more channels, in addition to more 15-second commercials (Kent 1993, 1995), has led to the high clutter levels observed today, not to mention the high cost of television advertising, with the average 30-second prime-time commercial on network television now costing more than $300,000 (Katz 2003, p. 64).

Aaker and Carmen (1982) found evidence of overadvertising more than 20 years ago, and the situation today is considerably worse (Green 2003). Our results show that in this environment of increasing competitive clutter, advertising effectiveness will continue to decline. As Kent (1995, p. 55) comments, "Advertisers can't bring back the low-clutter television environment, but they can modify their tactics to increase ad effectiveness in the present context." A suggestion he offers is to buy more spot and less network television. However, spot television is no panacea for interference effects; our spot television data in Chicago exhibit competitive interference of sufficient magnitude to deflate advertising response.

Because we find that the biggest driver of competitive interference is not so much the weight of advertising but the number of competing advertisers, a useful tactic is to anticipate when competitors are going to advertise and choose to advertise when they do not. A way to execute this is to identify markets in which there are fewer competitor brands advertising. Schroer (1990) illustrates this point with an example from the beer market in Iowa. In the early 1980s, Pabst and Old Milwaukee spent less on advertising, allowing many periods during which Anheuser-Busch was the sole advertiser. Thus, instead of three brands advertising, just one was advertising at high levels. Over a two-year period, Busch's share increased by 10 percentage points, and Pabst's and Old Milwaukee's share declined by 13 and 8 percentage points, respectively.

Another media planning strategy is to concentrate advertising into one- or two-day bursts within a week rather than spread it over the full week. Using a large single-source panel in the United Kingdom, Roberts (1999) finds that three exposures to an advertisement on the same day results in a much greater sales lift than three exposures spread out over three days. If competitors are spreading their advertising over the week, concentrating the advertising of the focal brand to one day will result in less competitive interference effects on that day. The key is to choose that day so that it is close to actual purchase. Our analysis of two hypothetical advertising strategies—(1) always match and (2) always avoid competitors' advertising—shows that achieving a period of exclusive advertising results in greater sales gains. This is consistent with Schroer's (1990) and Roberts's (1999) marketplace examples.

Many of the brands in our study are produced by large "umbrella" manufacturers, such as Procter & Gamble and Kelloggs. There are opportunities for the various brands that belong to these manufacturers to coordinate their advertising to help reduce interference among their own brands. There were no obvious signs of such coordination in our data, so there is scope for more mutually beneficial media planning in the future.

The previous media planning suggestions are aimed at avoiding advertising interference. Conversely, a brand may deliberately make use of this attenuation to "blunt the sword" of its competitors' advertising efforts. Some evidence of this is apparent for Tide in our empirical example. Its own-brand pure ad elasticity is not significant. However, it has significant, negative cross-brand ad elasticities with two of its competitors and is one of the heaviest advertisers in the category. Thus, although Tide appears to gain no direct benefits from its own advertising, it gains indirect benefits by suppressing the ad effectiveness of some of its competitors.

Although our study is comprehensive, it is not without its limitations. We study just one retail chain within a large metropolitan area. Moreover, our advertising data are limited to just spot television rather than all television outlets. Despite these limitations, we believe that our study provides a good starting point for further work. For example, future studies could extend our range of categories, grocery chains, and markets to ensure a consistent finding—namely, that increasing levels of competitor advertising are substantially dampening advertising response for a focal brand. In addition, subsequent models might allow for different clutter parameters for each brand. Further research might extend the work of Naik, Matrala, and Sawyer (1998) and Dubé, Hitsch, and Manchanda (2005) on advertising pulsing schedules but incorporate competitive interference. Our study also invites the possibility of further work using a game-theoretic approach to optimal advertising spending (Erickson 1995, 1997) because it is likely that current advertising spending levels are too high in many categories. Alternatively, there may be a win–win equilibrium level of advertising among competing firms, with different ad spending depending on firm size.

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