

5-2004

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The Effect of Competitive Advertising Interference on Sales for Packaged Goods

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The authors thank Jeff Herrmann from Nielsen Media Research for supplying the television ratings data and the Kilts Center of Marketing at the GSB, University of Chicago for the Dominick's Finer Food data.

7 May 2004

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ABSTRACT

Competitive advertising interference arises when viewers of advertising for a focal brand are also exposed to advertising messages for competing brands within a short time period, say one week for TV advertising. Although competitive advertising interference has been shown to reduce ad recall and recognition and brand evaluation measures, no studies have examined the impact on sales. In this research we use a market response model of sales for two grocery categories in the Chicago area to investigate possible advertising interference effects. The results show that competitive interference effects 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 rate of decrease depends on the number of competing brands advertising in a particular week and their total GRPs broadcast. We are able to derive optimal advertising levels for the brands within a category so that they all have the maximum sales response from advertising. It transpires that the current level of television advertising within the two categories is much higher than this optimum level, indicating that these grocery brands are likely to be over advertising at present. Curtailing advertising for all the brands would increase the response to advertising for each of them.

INTRODUCTION

In 1997 television advertising expenditure in the US was \$42 billion. Only 5 years later expenditure was over \$58 billion, a 38% increase, being 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 over 16 minutes per hour in prime time (Electronic Media 2002). Nonprogram minutes in daytime television is even higher, being nearly 21 minutes each hour.

The downstream effect of increased advertising on television viewers is obvious; they are exposed to many more ads, potentially reducing 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 TV exposures per week per person, the Millward Brown awareness index is 150 (compared with the UK benchmark of 100). However, in Italy, where there are 300 average exposures per week per person, the average awareness index drops to only 50. Clearly one effect of increasing advertising levels is to decrease the recall of all ads. Academic studies have also 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 is also increasing ad avoidance behavior (Danaher 1995; Lafayette 2004; Yorke and Kitchen 1985; Van Meurs 1998), such as channel switching or time-shift viewing with a PVR (Green 2003).

A commonly used term to describe 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 biggest 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 ads delivered by competing brands 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 affect on ad recall than noncompetitive clutter. In this study we focus on just competitive clutter.

Most previous research on advertising interference has been restricted to student samples with subjects exposed to commercials in a laboratory setting (Burke and Srull 1988; Keller 1991; Kent and Allen 1994), resulting in low external validity. A further limitation is the use of unfamiliar brands, which Kent and Allen (1994) show are more prone to interference effects. Lastly, all the previous marketing studies have looked at 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 paper is to make up for these shortcomings by examining the effect of competitive interference on sales for well-known brands within two grocery categories in a major U.S. metropolitan market.

RELEVANT LITERATURE

The prevalence of competitive clutter in U.S. television is evidenced by Kent (1995), who reports that in daytime network TV about 31 ads are broadcast per hour. Furthermore, depending on the network, somewhere between 19 and 29 percent of ads have a competitive commercial aired within the same hour on the same channel. This percentage rises to between

23 and 35 percent during prime time, although fewer ads are broadcast in this time zone. Obviously, over a longer time period, such as a week, most ads will be subject to interference effects from their competitors.

The harmful effect of such high competitive clutter on consumer advertising response has been known to marketers for some time (Bettman 1979; Bagozzi and Silk 1983). While early experimental work by Webb (1979) demonstrates that increased clutter levels reduce brand name recall, Brown and Rothschild (1993) found 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. Hence, a key environmental factor on the effect of clutter is the presence of competing 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 by other learning. Time effects, such as advertising decay or wearout (Axelrod 1980) are often incorporated in advertising response models (e.g., Little 1979; Lodish 1971). However, the passing of time is not the only reason for a decrease in advertising response. Early experiments in psychology, that have controlled for time effects, suggest that much of the "forgetting" is due to additional learning, rather than time passing (McGeoch 1932).

Thus, information from advertising can be "unlearned" because of subsequent exposure to competing brands' messages. This is known as retroactive, as opposed to 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, both prior and subsequent to exposure to advertising from competing brands. Keller (1987) finds that proactive competitive interference also inhibits ad and brand recall, but could not demonstrate any impact of competitive interference on brand evaluations (being ad and brand

attitude and purchase intentions). However, a follow up experiment by Keller (1991) was able to demonstrate the detrimental effects of competitive interference on brand evaluations. His study also showed that interference effects are alleviated by using advertising retrieval cues in the form of executional information from the original ad.

Interference effects are generally perceived as deleterious to advertising effectiveness, but in a recent study Jewell and Unnava (2003) exploited interference effects in the situation where 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, in fact, rather helpful.

Previous research on competitive interference has a number of limitations, which we now detail. First, Burke and Srull (1988), Keller (1987; 1991) and Kent and Allen (1994) all used student samples or convenience samples in a near forced-exposure situation in a laboratory setting. Second, these same studies exposed subjects to just commercials, without embedding them in a realistic media viewing environment with program or editorial material. Therefore, subjects 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 3 or 4 competitive ads per brand, whereas actual exposure levels in today's TV environment are generally much higher (Kent 1995). Fourth, Kent and Allen (1994) identify that a further external validity problem for the studies by Burke and Srull (1988) and Keller (1987; 1991) 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. Lastly, all previous studies have looked at the effect of competitive

interference on recall, recognition or brand evaluations rather than sales¹. Sales, as a criterion for advertising effectiveness is clearly of much interest to advertisers (East 2003, p. 19).

Our research aims to correct for the limitations of previous research. Specifically, we use actual weekly sales and spot TV advertising data for the Chicago area in 1991. We examine seven brands in the liquid laundry detergent category and 18 brands in the ready to eat cereal category. Kent (1995) identified these two categories as being among the top ten categories with the most competitive clutter. Additionally, we use Nielsen television ratings data for this period to establish the weekly audience size (measured in gross rating points) for each brand that advertises. After demonstrating that competitive advertising reduces the response to advertising, we proceed to show the appropriate levels of advertising that each brand should have to maximize its sales. In general, this level is somewhat lower than the current advertising volume, indicating that brands tend to be over-advertising.

The paper proceeds as follows. We firstly develop a sales response model suitable for our weekly sales data. The model allows for all the marketing mix factors that potentially impact on sales. Second, we construct a reasonable measure of competitive clutter that allows for the number of competing brands that simultaneously advertise and the volume of their advertising. Third, we fit the model to two grocery categories and test to see if competitive clutter influences advertising response. Fourth, we use the fitted model to see what level of competitive advertising maximizes sales for a focal brand and all the brands in a category. We conclude with some advice about how advertisers might reduce the effects of advertising interference on their brands.

¹ One earlier study by Metwally (1978) did look at whether competing brands react to each others TV 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 using 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.

METHOD

Model Relating Marketing Effort to Sales

While the primary purpose of this study is to examine the effect of competitive advertising on sales we cannot ignore the effects of other marketing factors on sales. Our model must also be tailored to the data, which is weekly scanner data spanning a one year period. For instance a multinomial-logit model, as developed by Guadagni and Little (1983), is not appropriate here since such a model requires individual-level data. There is a long history of econometric models developed for use on weekly scanner data (Leeflang et al 2000), including several used commercially, such as SCAN*PRO (Wittink et al 1988) and PROMOTIONSCAN (Abraham and Lodish 1993). Leeflang et al (2000, p.74) report that one of the most frequently encountered sales response models is the so-called multiplicative model. Here sales are related to marketing variables via the following functional form,

$$Sales_{it} = \left(\prod_{m=1}^M (x_{it}^m)^{\beta_m} \right) \exp(\varepsilon_{it}),$$

where $\mathbf{x}_{it} = (x_{it}^1, x_{it}^2, \dots, x_{it}^M)$ is a vector of M covariates with associated parameter vector

$\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_M)$, where i ranges from 1 to B brands within a category, t ranges from 1 to T time periods and ε_{it} is a random error term. By taking the log of both sides we obtain

$$(1) \quad \log(Sales_{it}) = \sum_{m=1}^M \beta_m \log(x_{it}^m) + \varepsilon_{it}$$

An appealing feature of the model in equation (1) is that the elasticity for the m^{th} covariate is simply β_m . For instance, an estimate of the advertising elasticity follows directly from the corresponding estimated parameter. The relative magnitude of the elasticities also gives an indication of the relative responsiveness of consumers to alternative marketing efforts, such as price changes versus local area advertising. For example, Leone & Schultz (1980) find

that advertising has a small, but positive effect on sales, while Blattberg et al (1995) report that temporary price reductions have a relatively much stronger effect. Other frequently observed advertising phenomenon include diminishing returns (Simon 1970) and carryover effects (Leone 1995).

With time series data of weekly sales it is reasonable to expect serial correlation from one week to the next (Jacobson 1990), in which case the error term in equation (1) is better modeled by

$$\varepsilon_{it} = \rho\varepsilon_{it-1} + u_{it},$$

where $|\rho| < 1$ and u_{it} is a random disturbance, distributed normally with mean zero and variance σ^2 .

Since competitive clutter is obviously a phenomenon that permeates across the category as well as for individual brands, we analyze the sales data for the whole category together, rather than for each brand separately. That said, the average sales levels might differ across brands. Furthermore, there might be unobservable brand effects for factors that are not measured in our data, such as the proportion of stores in the target area that stock each brand. Boulding (1990) suggests that a good model to simultaneously handle autocorrelation and brand specific effects has the following error structure

$$(2) \quad \varepsilon_{it} = \rho\varepsilon_{it-1} + \alpha_i + u_{it}.$$

Combining the sales model in (1) with the error structure in (2) gives a regression-type model of the form

$$(3) \quad \log(\text{Sales}_{it}) = \rho \log(\text{Sales}_{it-1}) + \sum_{m=1}^M \beta_m (\log(x_{it}^m) - \rho \log(x_{it-1}^m)) + \alpha_i + u_{it}.$$

The α_i parameter set can be operationalized simply as $B-1$ dummy variables for the B brands in the category.

Our data comprise branded packaged goods sold in grocery stores. As a result, the covariates include factors known to affect sales such as price, in-store promotion, price discounts and television advertising (Blattberg 1995). Price and in-store promotions are well-known to have a rapid and strong affect on sales (Blattberg 1995, Guadagni and Little 1983). In this study our primary focus is on advertising's effect on sales, for which there has been considerable research in the marketing arena (see, for example, Bass and Leone 1983; Leeflang et al 2000; Leone and Shultz 1980). When relating advertising to downstream sales with time-series data there is a potential endogeneity problem. This manifests itself because advertising budgets for future years are often set at a fixed proportion of current-year sales (Leeflang et al 2000, p. 377). One way to allow for this problem is to use a simultaneous equation approach, such as 2SLS or use instrumental variables (Greene 1997, p.288). However, in our case, we have weekly rather than annual data, where it is much less likely that endogeneity issues will arise (Leeflang et al 2000, p. 382). For this reason, we do not use a simultaneous equation approach here.

Another documented effect of advertising's impact on sales is advertising carryover (Clarke 1976). Here, advertising in a previous time period affects sales in the current and possibly future time periods. A popular method for handling such advertising carryover is to use the Koyck distributed lag model (Leone 1995). Incorporating distributed lags for advertising with the Koyck model is inconsistent with the model in equation (3). Instead, we can simply add further covariate terms in equation (3) corresponding to previous weeks of advertising. In our case, advertising often comes in four week 'bursts' so we might reasonably include three lagged advertising terms among the covariates in equation (3). Later, we show empirically that such lagged terms are unnecessary in our two categories.

Clutter's Affect on Advertising Elasticity

We noted earlier for equation (3) that the elasticity for marketing factor m is simply the corresponding regression coefficient β_m . Leone and Schultz (1980) report advertising elasticities for packaged goods in the range 0.003 to 0.23. If competitive clutter effects are present, we would expect attenuation in the advertising elasticity (Burke and Srull 1988; Keller 1987; 1991; Kent and Allen 1994). That is, a brand's advertising elasticity becomes lower than it would be if none of its competitors were simultaneously advertising. Such advertising attenuation is expected to increase as the quantity of competitive clutter increases. Conversely, for low levels of competitive clutter, we expect little affect on a brand's advertising elasticity. Such a situation is consistent with a reverse-S shape function which is easily modeled by a logistic function (Leeflang et al 2000, p.80).

Denote the advertising elasticity in equation (3) as β_{adv} . We model this, in turn, as a function of competitive clutter and a 'pure' advertising elasticity, that is, the advertising elasticity that would exist in the presence of no competitive clutter. Specifically we have

$$(4) \quad \beta_{adv} = e^{\delta} \frac{e^{\gamma_1 + \gamma_2 C}}{1 + e^{\gamma_1 + \gamma_2 C}},$$

where C denotes competitive clutter (to be defined later) and δ, γ_1 and γ_2 are parameters to be estimated.

Consider firstly the logistic function part of equation (4), namely, $\frac{e^{\gamma_1 + \gamma_2 C}}{1 + e^{\gamma_1 + \gamma_2 C}}$. When $C = 0$ and $\gamma_1 > 4$ the logistic component is greater than 0.98, being very close to 1. If competitive clutter effects do, in fact, attenuate advertising elasticity then $\gamma_2 < 0$, in which case the logistic component of β_{adv} clearly decreases to zero as C increases. When competitive clutter is zero and $\gamma_1 > 4$ we have $\beta_{adv} \approx e^{\delta}$. Hence, e^{δ} can be thought of as the

‘pure’ advertising elasticity, the sales response to advertising when no competitive clutter effects are present. We parameterize this ‘pure’ advertising elasticity as e^δ to ensure that it is positive, as Leone and Shultz (1980) find that advertising elasticity is usually less than 1, but positive, in which case we expect $\delta < 0$.

We also tried a simple exponential decay model for advertising elasticity, namely, $\beta_{adv} = e^\delta e^{\gamma_2 C}$, but found this did not fit the data as well as the logistic model in equation (4).

Brand Heterogeneity

Heterogeneity is often observed in marketing contexts (Allenby and Rossi 1999), although it is usually a feature of survey or panel respondents rather than brands *per se*. However, in our setting it is reasonable to anticipate that response to price promotions and advertising may vary across the brands within a category. A simple way to handle this potential heterogeneity is to allow the β_m regression coefficients in equation (3) to be random effects, as is frequently assumed in a hierarchical Bayes model (Allenby and Rossi 1999). It might be argued that we have already allowed for differences among brands by including brand-level dummy variables in our model in equation (3). However, as noted above, we included the fixed effect brand dummy variables to allow for unobserved brand-level effects. Covariates like price and price cut are observed variables that might still differ across brands even with brand-level fixed effects included in the model. Hence, we permit the β_m coefficients to be random variables from a normal distribution with mean $\bar{\beta}_m$, as in a traditional random effects model (Laird and Ware 1982).

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, TV program promotions and

public service announcements. As mentioned above, we focus on just competitive clutter, sometimes referred to as interference (Burke and Srull 1988; Kent and Allen 1994).

Television competitive clutter is commercials that are broadcast at the same or similar time as a focal brand, either accidentally or deliberately, with the intention to dilute the effectiveness of the focal brand.

In a packaged goods category with B brands, clutter increases as more brands advertise at increasingly higher levels. One possible definition of clutter might be the total number of ads for the entire category that are broadcast in a particular week. However, suppose that just the focal brand is advertising, with no other brands advertising that week. Even if this brand increases its advertising to very high levels, this should not reduce its advertising elasticity. Certainly, there will be diminishing returns to advertising, but it is unlikely that sales of the brand will actually decrease when just that one brand is advertising heavily (Rossiter and Danaher 1998, p. 27). For this reason we conceptualize competitive clutter as being a feature only of competitor advertising rather than focal-brand advertising². In addition, it is apparent that clutter effects will be stronger if more brands are advertising simultaneously (Burke and Srull 1988; D'Souza and Rao 1995; Kent and Allen 1994). For example, when all ten brands in a category comprised of ten brands are advertising in the same week, consumers will receive more confused messages than if just two of the brands advertise that week. Hence, competitive clutter is really a combination of the proportion of competitor brands advertising in the category and the total amount of advertising these brands deliver. 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 gross rating points (GRPs), which is the sum of ratings achieved across each advertising spot,

² 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 (4), since the focal brand's advertising would then be one of the independent variables in the model of equation (3) and would also be present in the regression coefficient for that independent variable.

sometimes referred to as advertising weight. GRPs are the buying and selling currency of television advertising (Sissors and Baron 2002). We then define competitive clutter to be

$$(5) \quad C_{it} = \left(\frac{\sum_{j \neq i} I_{\{A_{jt}\}}}{B-1} \right) \sum_{j \neq i} A_{jt} ,$$

where $I_{\{A_{jt}\}} = 1$ if $A_{jt} > 0$, i.e., if brand j advertises in week t , and is 0 otherwise. Hence, C_{it} is the product of the proportion of competing brands that are advertising and the total advertising volume of these competing brands. Competitive clutter will be high when a large proportion of competitor brands advertise at heavy levels at the same time the focal brand is advertising. Later we show that a model with both the proportion component of equation (5) and the total advertising volume component gives an improved fit compared with a model which contains either one of the two components.

In our application C_{it} ranges from 0.166 to 427, with a right-skewed distribution, so we take the log of C_{it} to reduce the high skew, as suggested by Mosteller and Tukey (1977). Therefore, our final model for the advertising elasticity in equation (4) is

$$(6) \quad \beta_{adv} = e^{\delta} \frac{e^{\gamma_1 + \gamma_2 \log C_{it}}}{1 + e^{\gamma_1 + \gamma_2 \log C_{it}}} .$$

As for price and promotion, we allow for differing advertising response across brands, by assuming δ is a random effect, being normally distributed with mean $\bar{\delta}$.

SOURCES OF DATA

Our model in equation (3) is essentially a sales response model where sales are modeled as a function of marketing mix covariates. To fit this model 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 TV 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 firstly describe the source of our sales, price and in-store promotion data then describe the television advertising data, followed by the TV ratings data.

Sales Data

Our sales data come from the well-known Chicago supermarket chain, Dominick’s Finer Foods (DFF). DFF has 86 stores spread throughout the Chicago metropolitan area, accounting for about 20% of the region’s grocery market. Although DFF sales are not a census of all grocery sales in Chicago, the more relevant issue is how well DFF represents sales for the region. Hoch et al (1995) give a map of the distribution of DFF stores, which clearly shows they are spread over the length and breadth of Chicago, with concentrations in the more densely populated areas. Hence, it is reasonable to assume that sales from DFF stores are representative of grocery store sales for the Chicago metropolitan area³.

We examine two categories in detail, being liquid laundry detergent and ready-to-eat (RTE) plain cereals. Kent (1995) identified RTE cereals and household products (such as laundry detergent) as 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 7 brands, while RTE cereals has 18 brands, listed respectively in Tables 1a and 1b. To accommodate different package sizes, the detergent sales data are based on volume sold, with

³Denote total weekly DFF sales for brand i in week t as S_{it} . Since DFF sales are 20% of the entire market, total weekly sales across all stores is $5 \times S_{it}$. Hence, when reweighting the sales data all that changes in equation (3) is that a term $(\rho - 1)\log(5)$ is added to the right hand side. This is simply an adjustment of the intercept term and affects no other parameters in the model.

a standard size being IRI's "equivalent unit" of 16 fluid ounces. For cereals, IRI's "equivalent unit" is a weight of 16 ounces. The market share for the detergent brands in Table 1a is based on volume sales in fluid ounces, with Tide being the dominant brand in the category. With the larger number of brands in the cereals category, only three brands have double-digit market share.

The average price for detergent is also based on IRI's "equivalent unit" of 16 fluid ounces. Hence, for example, the average price of 64 fl. oz. Tide is $\$1.014 \times 4 = \4.06 . We also include measures of each brand's in-store promotional activities. In the data they are coded simply as the presence or absence of a promotion for a given SKU in a given store. To aggregate to the region-brand level we sum the number of promoted SKUs across each of the stores. For example, if in a given week, all 86 stores each promote 1 SKU of Tide with a self-tag price reduction (often in the form of a 'buy-one-get-some-free' deal) the 'bonus' number is 86. The 'price-off' promotion variable uses the same construction as 'bonus', but indicates the presence or absence of a straightforward price discount.

Advertising Data

Advertising for national brands such as those in Table 1 can potentially be in media such as radio, magazines, newspapers and television⁴. Given that competitive clutter is considered to be 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 LNA (1992) report of leading national advertisers for the year of 1991 shows that in the liquid laundry detergent category, Procter & Gamble and Unilever⁵ allocate 86% and 76%, respectively, of their total advertising budget to just television. Of the brands in Table 1a, only Tide has any significant non-television advertising

⁴ 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.

⁵ Unilever manufacture the brands All and Surf, while Procter & Gamble manufacture all of the other five detergent brands in Table 1a.

expenditure. For the RTE cereals category, the average proportion of advertising budget allocated to television for the five manufacturers in Table 1b is 83%. This is particularly true for General Mills and Kelloggs, both of whose television allocation exceeds 95% of their combined advertising budget. Therefore, it is reasonable to use advertising data only for television, as it is the dominant medium for our two product categories.

We further split television advertising into spot TV and other television advertising (network, syndicated and cable). We focus on just spot TV advertising data for several reasons. First, spot TV has much shorter purchasing lead times (two weeks to two months) than network TV advertising, which is typically bought 3-12 months in advance (Sissors and Baron 2002). This enables rapid tactical use of advertising either offensively or defensively. Second, spot TV permits the purchasing of particular programs and stations, whereas network and syndicated TV is generally bought in broad dayparts for all the affiliate stations (Katz 2003). Therefore, with network and syndicated TV the advertiser has limited control over the program and advertising pod placement, making these media less attractive for competitive advertising. Third, network television usually has policies that reduce the amount of competitive interference by restricting the occurrence of ads being broadcast by competitors within a short time frame (Kent 1993; 1995). Fourth, cable television is omitted due to its fragmented audiences and low ratings. It is not a suitable medium for products with general appeal, such as detergents and RTE cereals. Hence, if brands want to interfere with their competitors' advertising then spot TV is the ideal medium to examine.

The LNA (1992) report does not separate out television advertising expenditure by individual brands, but does say how much was spent by each manufacturer. For instance, it reports that Procter & Gamble and Unilever allocate 28% and 30%, respectively, of their TV spend to spot TV. For cereals, four of the five manufacturers allocate between 20% and 30%

of their TV budget to spot TV. Only General Mills shows significant variance among RTE cereals manufacturers, by allocating 51% of its television advertising to spot TV.

Even though spot TV represents about one-third of total television spend for these manufacturers, on average, a more critical issue is whether or not spot TV is representative of a brand's total TV spend. If this is true, and we have no reason to doubt it, we can simply adjust the levels of spot TV advertising spend for each manufacturer according to the proportion of their total spend allocated to spot TV. For instance, this entails dividing the Unilever spot TV spend by 0.3 to get a reasonable estimate of its total television advertising levels. Later, we refit our model with adjusted advertising weight to see what effect this has on the parameter estimates.

Our spot TV advertising data come from Arbitron's television commercial monitoring service, the Broadcast Advertising Reports, for the same year as our sales data, namely, 1991. This service monitors the principle commercial TV 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.

TV Ratings Data

At this stage our data have only the total number of advertising spots that each brand broadcasts every week. Obviously not all spots carry the same weight in terms of audience size. In general, a late night spot will not have the same audience 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 is known as Gross Ratings Points (GRPs), which is the 'currency' for television advertising (Katz 2003; Sissors and Baron 2002).

The ratings data from Nielsen Media Research are based on a sample of about 2000 households in the Chicago Designated Market Area. Around 375 households complete a quarter-hour television diary for a one week period over a four week period, giving a total of 1500 diary households. A further 500 households have peplemeters installed for continuous measurement. Data are reported across four weeks corresponding to quarterly “sweeps” in February, May, July 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, March; the May sweep covers programs shown in April, May and June, and so on. Even though diary-based ratings are collected only in February of the first quarter, due to 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 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. Since the quarterly sweeps do not necessarily cover the month for which we have advertising data (e.g., our February ratings data does 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 that the program is shown. In other cases, the programming may have changed from the month in which the sweep was performed. In these cases we also take the typical ratings for that quarter. Only 250 (8%) advertising spot ratings were estimated in this way. In cases where an advertisement is placed in a “break” between programs, we use the average rating of the programs surrounding the break.

RESULTS

Parameter Estimates

Using the marketing variables described in equation (3), with the advertising elasticity coefficient in equation (6), results in our final model⁶, given by

$$(7)$$

$$\log(\text{Sales}_{it}) = \rho \log(\text{Sales}_{it-1}) + \beta_0(1 - \rho) + \beta_{price}(\log(\text{Price}_{it}) - \rho \log(\text{Price}_{it-1})) + \beta_{bonus}(\log(\text{Bonus}_{it}) - \rho \log(\text{Bonus}_{it-1})) + \beta_{priceoff}(\log(\text{PriceOff}_{it}) - \rho \log(\text{PriceOff}_{it-1})) + e^{\delta} \frac{e^{\gamma_1 + \gamma_2 \log C_{it}}}{1 + e^{\gamma_1 + \gamma_2 \log C_{it}}}(\log(\text{Adv}_{it}) - \rho \log(\text{Adv}_{it-1})) + \text{brand_dummies} + u_{it}.$$

Our initial model had three lagged advertising variables (with corresponding clutter elasticities as in equation (6)). However, since none of these lagged advertising variables are significant we drop them from the model. The final model with random coefficients for β_{price} , β_{bonus} , $\beta_{priceoff}$ and δ was fit using WinBUGS v1.4 (Spiegelhalter et al 2003) with 10,000 burn-in iterations and 10,000 estimation iterations over two Markov chains. The Gelman and Rubin (1992) statistic showed the parameter estimates converged extremely well to steady state values.

The estimated parameters and their standard errors are given in Tables 2 and 3, respectively, for laundry detergent and RTE cereals. Since β_{price} , β_{bonus} , $\beta_{priceoff}$ and δ are random effects we report the mean of their respective distributions and label these means as $\bar{\beta}_{price}$, $\bar{\beta}_{bonus}$, $\bar{\beta}_{priceoff}$ and $\bar{\delta}$. All of the parameters are significant at the 5% level or lower for detergents and RTE cereals, apart from three of the brand dummy variable parameters for cereals. Turning attention to the marketing mix covariates for both categories, they all have the anticipated sign, with the elasticity for price being large and negative⁷, while those for bonus and price-off are positive, but much smaller in magnitude. We also note that the

⁶ We set the baseline brand dummy to be zero for Tide in the laundry detergent category and Wheaties in the RTE cereal category.

⁷ As a double check, we also tried relative price instead of own-price and obtained a very similar price elasticity.

parameter for serial correlation (ρ) is significant, although not so close to one as to raise concerns about non-stationarity in the time series. The overall fit of the model appears to be very good, as a null model with just an intercept has a log-likelihood of -591.0. This gives a McFadden's (1974) ρ^2 value of $1 - 59.9/591.0 = 89.9\%$ for laundry detergents and $1 - 86.0/1222.2 = 93.0\%$ for cereals. Both are encouragingly high.

Of most interest to us are the parameters associated with β_{adv} as given in equation (4). Focusing on the laundry detergents category, the estimated δ value of -3.341 shows that the 'pure' advertising elasticity is $e^{-3.341} = 0.035$. This is in the range of advertising elasticities reported for branded packed goods by Leone and Schultz (1980), but is much smaller than the price elasticity, as expected. The estimated values of γ_1 and γ_2 at 4.929 and -0.982, respectively, are of the magnitude anticipated above, which result in a reverse-S shaped logistic distribution.

We also fit our model using two alternative definitions of competitive clutter, one being the proportion of competitor brands advertising and the other being the total competitor GRPs, which are the two respective components of equation (5). Since these models use different data they are not nested within the model using equation (5) as the definition of competitive clutter. In nonnested cases like this Spiegelhalter et al (2003) demonstrate that is appropriate to use their DIC measure of model comparison, with the model having the smallest DIC being best. The DIC for the combined model of competitive clutter is 135.2, while those for the respective subcomponents are 136.8 and 135.9. We also fitted a third alternative model that had separate parameters for the two clutter components in equation (5), having γ_2 and γ_3 parameters instead of just γ_2 . This DIC for this model is 135.7, with the estimates of γ_2 and γ_3 being almost identical (-.967 and -.989, respectively). Since the DIC values for the subcomponent-only models and the separate components model are all higher

than 135.2, we conclude that it is best to combine the proportion of competing brands and their total competing advertising volume, as done in equation (5). A similar finding occurs in the RTE cereals category.

Adjustment of Spot TV GRPs

Recall from our discussion of the advertising data that we use only spot TV. For Procter and Gamble 28% of TV ad spend is on spot TV, while the percentage for Unilever is 30%. To examine the sensitivity of our model and results to advertising volume, we refitted the model in equation (7) but with the GRPs of Procter and Gamble and Unilever brands divided, respectively, by 0.28 and 0.3. This corrects for the shortfall in advertising volume that occurs due to our use of just spot TV.

The effect of this correction can be anticipated using equation (7), where if we multiply A_{it} and C_{it} by a constant θ (being say $1/0.29$, the inverse of the average of 0.28 and 0.3 spot TV proportions), the component for advertising becomes

$$\begin{aligned} & e^{\delta} \frac{e^{\gamma_1 + \gamma_2 \log \theta C_{it}}}{1 + e^{\gamma_1 + \gamma_2 \log \theta C_{it}}} (\log(\theta Adv_{it}) - \rho \log(\theta Adv_{it-1})) \\ &= e^{\delta} \frac{e^{\gamma'_1 + \gamma_2 \log C_{it}}}{1 + e^{\gamma'_1 + \gamma_2 \log C_{it}}} (1 - \rho) \log(\theta) + e^{\delta} \frac{e^{\gamma'_1 + \gamma_2 \log C_{it}}}{1 + e^{\gamma'_1 + \gamma_2 \log C_{it}}} (\log(Adv_{it}) - \rho \log(Adv_{it-1})), \end{aligned}$$

where $\gamma'_1 = \gamma_1 + \gamma_2 \log(\theta)$. Since the first term on the right hand side is close to zero (being 0.017 for laundry detergents), the only major change to the advertising component of equation (7) is that γ_1 is adjusted to become $\gamma_1 + \gamma_2 \log(\theta)$. The parameter estimates from Table 2 allow us to estimate the adjusted γ_1 as $\hat{\gamma}'_1 = 4.929 - 0.982 \log(1/.29) = 3.71$. We now refit the entire model in equation (7) using the adjusted values of A_{it} and C_{it} . The new estimates of γ_1 and γ_2 are, respectively, 3.72 and -1.021. These new estimates are nearly perfectly in line with our predictions, namely, that γ_1 changes by a factor of $\gamma_2 \log(\theta)$

(predicted value of 3.71 versus new estimate of 3.72) and γ_2 is largely unchanged (predicted value of -0.982 versus new estimate of -1.021). That is, using just spot TV does not materially affect the estimate of γ_2 , with the significant negative effect of competitive clutter still being prevalent.

Clutter's Effect on Advertising Elasticity

Figure 1 shows the effect of increasing competitive clutter on the advertising elasticity in the laundry detergent category. Clearly, beyond a competitive clutter level of $\exp(2)=7.4$ the advertising elasticity starts to fall quickly. Table 1a shows that the average competitive clutter level for this category is 133.2. At this level of clutter, Figure 1 gives an estimated advertising elasticity of 0.019. However, when there is no competitive clutter the advertising elasticity is nearly two times higher, at 0.035, showing the deleterious effects of competitive interference. To underscore this attenuating effect of competitive clutter, we re-estimated the model in equation (7), but with just a single regression-type parameter for advertising, as for the other marketing variables. The estimated value of the advertising elasticity in this model is 0.018, being very close to the 0.019 obtained at the average clutter level in Figure 1 (at the point $\log(133.2)= 4.892$). What this means is that if competitive clutter effects are ignored and we naively estimate the advertising elasticity, a value of 0.018 is obtained, which is relatively low (Leone and Schultz 1980). However, the advertising elasticity without clutter is 0.035. Clearly, competitive clutter masks the true effect advertising can have on sales.

ADVERTISING AND CLUTTER EFFECTS ON SALES

We saw above how increasing competitive clutter levels reduces advertising elasticity and thereby diminishes the effect that advertising has on sales. In this section we focus on just advertising's effect on sales and assume the other marketing mix factors are held constant. To illustrate the effect of clutter on sales we calculate the log of sales for an

‘average brand’ in the laundry detergent category. This is achieved by substituting the average of the log(price), log(price-off) and log(bonus) covariates as well as the estimated parameters from Table 2 into equation (1). We also use the average of the brand dummy variable parameter estimates to allow for the error structure in equation (2). As a reference point, the log of sales calculated at the average value of competitive clutter and for the average of log(advertising) across all the brands is 10.2. We now examine the change in the log of sales with respect to this reference point, which has an expected value of

$$(8) \quad \Delta \log(\text{Sales}) = e^{\hat{\delta}} \frac{e^{\hat{\gamma}_1 + \hat{\gamma}_2 \log C}}{1 + e^{\hat{\gamma}_1 + \hat{\gamma}_2 \log C}} \log(\text{GRP}_F),$$

where GRP_F are the GRPs for the focal brand and C is the competitive clutter, based on the number of competing brands advertising and their respective GRPs.

Equation (8) shows that when C is held constant, increasing GRP_F for the focal brand will increase its sales. However, the amount by which its sales increase very much depends on the competitive clutter, with high levels resulting in lower sales lift. Figure 2a uses equation (8) to plot $\Delta \log(\text{Sales})$ when just two of the seven brands are advertising, the focal brand and one other. The diminishing return of sales to increasing advertising for the focal brand is apparent. Also note that as the number of GRPs for the other brand increases, the sales response to advertising for the focal brand declines, but not substantially.

Figure 2b shows $\Delta \log(\text{Sales})$ when three other brands are advertising in addition to the focal brand, while Figure 2c plots $\Delta \log(\text{Sales})$ when all 6 competing brands are advertising simultaneously against the focal brand. The drop in $\Delta \log(\text{Sales})$ from the two-brand situation is remarkable and highlights the dramatic effect that competitive interference can have on sales, especially as the proportion of brands advertising in the category increases. Only when the competitor brands advertise at very low levels can the focal brand expect to see a substantial response to their advertising. For example, when the six ‘other’ brands in

Figure 2c broadcast 150 total GRPs and the focal brand advertises at 50 GRPs, log sales for the focal brand increase by 0.027, being a 2.8% lift in sales. However, when the other six brands have a lower total of just 50 GRPs, matching the focal brand's 50 GRPs, the sales lift for the focal brand more than doubles to 6.4%.

Figures 2a through 2c also illustrate that competitive interference effects are heavily impacted by the proportion of brands simultaneously advertising. For instance, the sales increase when the focal brand advertises at 50 GRPs and 6 competing brands advertise at 25 GRPs each is 2.8%. However, for the same focal brand advertising of 50 GRPs, but when just 3 competing brands advertise at 50 GRPs each, the sales increase rises to 5.1%. That is, even though in both cases the total competitive GRPs are 150, bigger sales gains due to focal brand advertising can be expected when fewer competitors are advertising in the same week.

Optimal Advertising Levels Under Brand Cooperation

The previous section showed that even with relatively low competitor advertising levels, such as 25 GRPs per brand per week, there is a dramatic attenuation in the sales lift when the focal brand advertises. While one or more brands in a category may be intentionally trying to interfere with their competitors' advertising, others may not be aware of the deleterious effects of over-advertising in the category. Equation (8) shows that sales increase as advertising for a focal brand increases, but the sales increase is reduced as competitor clutter increases (if $\gamma_2 < 0$). In its present form, equation (8) has no functional relationship between a focal brand's advertising and that of its competitors. Suppose now that, within a category, b of the competitor brands cooperate with the focal brand by advertising with exactly the same number of GRPs as the focal brand, while the remaining $B - 1 - b$ brands do not advertise. Denote this common advertising GRP level as A . In this situation equation (8) becomes, for B brands in the category and $b \leq B - 1$,

$$(9) \quad \Delta \log(\text{Sales}) = e^{\hat{\delta}} \frac{\exp\left(\hat{\gamma}_1 + \hat{\gamma}_2 \log\left(\frac{b}{B-1} bA\right)\right)}{1 + \exp\left(\hat{\gamma}_1 + \hat{\gamma}_2 \log\left(\frac{b}{B-1} bA\right)\right)} \log(A).$$

Figure 3 is a graph of the right hand side of equation (9) for b varying from 1 to 6 and for A increasing upward from 5 GRPs, using the parameter estimates in Table 2 for laundry detergent. As previously seen, it shows that of the two components of ad clutter, the proportion of brands advertising in the category has a greater impact on sales attenuation than the number of competitive GRPs broadcast. This is illustrated by the very steep drop in $\Delta \log(\text{Sales})$ in going from 1 to 2 competitor brands advertising even at moderate levels of A .

Figure 3 also shows that there is a GRP level at which each brand will maximize the effectiveness of advertising on sales. By setting the derivative of equation (9) to zero, the maximum sales response occurs at A_M GRPs, which is the solution to the following equation

$$\exp\left(\hat{\gamma}_1 + \hat{\gamma}_2 \log\left(\frac{b}{B-1} bA_M\right)\right) = -1 - \hat{\gamma}_2 \log(A_M).$$

Table 4 gives the number of spot TV GRPs at which sales are maximized when b competitor brands in the category advertise at the same amount each week as the focal brand. The pattern in this table is clear, when there are many brands advertising (more than about two-thirds of the brands in the category), the optimal GRPs per brand is relatively low, at around 25 GRPs. This is generally much lower advertising weight than what we observe in the liquid laundry detergent category, where, for example, Table 1 shows that the average brand broadcasts 36 GRPs per week. This indicates that current sales levels due to advertising may be suboptimal.

To emphasize the point that present advertising levels in the laundry detergent category are suboptimal we calculate the number of times that brands in the detergent category are within 20% of the optimal GRP level, as prescribed by Table 4. For instance, if there are just two brands advertising in a particular week we looked to see if each brand, on

average, is advertising at levels within $209 \pm 0.2 \times 209 = (167, 251)$ GRPs. For five total brands (the focal brand and $b = 4$ competitors) the allowable interval is $26 \pm 0.2 \times 26$ GRPs, on average, for each brand. Of course, we omit the three weeks when only one brand advertises since there are no competitive interference effects in that case. It transpires that brands advertise within this near-optimal interval in only 70 of the $7 \times (52-3) = 343$ brand-weeks, that is, only 20.4% of brand-weeks. Even more revealing is that brands exceed the upper bound of the interval 59% of the time. That is, over-advertising is much more common than under-advertising. If the interval is generously widened to within $\pm 50\%$ of the optimal GRPs in Table 4, then the optimal advertising levels are achieved in only 37% of the brand-weeks and actual advertising levels exceed the upper bound 49% of the time. Clearly, the present levels of advertising in this laundry detergent category are far from that required to maximize the effectiveness of advertising on sales for each brand. In fact, if we substitute the actual GRPs per brand into A in equation (9), sales are 6.4% below those achievable when each brand advertises at the same optimum level.

Share of Voice

It is more common for brands to advertise in proportion to their market share rather than equally (Schroer 1990), so that a brand's share of voice (SOV) approximately equals its share of market (SOM). Figures 4a and 4b plot SOV against SOM for the laundry detergent and RTE cereals categories for the year of 1991⁸. Clearly the rule of thumb that SOV should equal SOM is operating in these categories, with most brands falling close to the SOV=SOM line. Some better-known brands, such as Tide, Kellogg's Corn Flakes and Cheerios enjoy a market share premium. On the other hand, Era Plus and Grape Nuts are probably trying to gain market share by advertising at higher levels than brands with comparable market share (Schroer 1990).

⁸ This time we base the SOV on the total national TV spend, not just spot TV in Chicago.

Schroer (1990) claims that share gain is possible only if a brand consistently outspends its competitor(s) by a two-to-one ratio of SOV. Our results show that advertising gains can also be made if advertisers search out gaps in their competitors' media plans. What is required is to identify markets where 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 instances where Anheuser-Busch was able to advertise solely for a short time period. Hence, instead of three brands advertising, just one was advertising at high levels. Over a two-year period, Busch's share increase by 10 percentage points while Pabst's and Old Milwaukee's share declined by 13 and 8 percentage points, respectively.

SUMMARY AND CONCLUSION

While previous research has found that advertising interference lowers ad recall, brand attitude and purchase intentions, no studies have examined the effect on sales. Our study addresses this shortcoming, with findings that are consistent with previous studies, showing that sales too are negatively impacted by competitive advertising interference. The result of advertising interference is attenuation in the advertising elasticity for the focal brand when competitors simultaneously advertise. For the liquid laundry detergent category the advertising elasticity is reduced by about one-half, while for RTE cereals the reduction is about 80%. The attenuation is worse for cereals as there are more brands and the category is less concentrated. Although advertisers have probably suspected that high levels of competitive interference reduces the effectiveness of their advertising on sales, until now the magnitude of the reduction has not been quantified. We now know that advertising response could be higher if there were less competitive interference within a category.

Previous experimental studies of advertising interference have found that familiar brands do not have the same drop in ad recall and recognition in the presence of competitive interference as fictitious or lesser-known brands (Kent and Allen 1993; 1994). In contrast, we find this does not carry through to sales, where even everyday brands like Tide, Surf, Cheerios and Corn Flakes have attenuated sales response when competitive interference is high.

Of course, experienced advertisers in mature markets, of which Procter and 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). Persistent use of the SOV=SOM strategy over the past forty years means 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), thereby increasing demand for advertising. The combination of higher demand with more channels, plus more 15 second commercials (Kent 1993; 1995), has led to the high clutter levels we see today, not to mention the high cost of television advertising, with the average 30 second prime time commercial on network TV now costing \$300,000 (Katz 2003, p. 64). This huge increase in television advertising has resulted in over-advertising to the point where if we compare present advertising levels with the optimum spend per brand, on average, brands overspend rather than under-spend each week by a three to one ratio.

As Kent (1995) 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". One suggestion he offers is to buy more spot and less network TV. However, spot TV is no panacea for interference effects, as our spot TV data in Chicago exhibit competitive interference of sufficient magnitude to deflate advertising response. Of course, network TV

has an even greater attenuation of ad response, but, nevertheless, spot TV is not immune from this problem.

Since 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. An obvious starting point is to look at historical advertising patterns of competitors. Another strategy is to concentrate advertising into one- or two-day bursts within a week rather than spread it over the full week. Roberts (1999), using a large single-source panel in the UK, finds that three exposures to an ad on the same day results in a much bigger sales lift than having three exposures spread over three days. If competitors are spreading their advertising over the week then 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 to be close to actual purchase.

We note that many of the brands in our study are produced by large ‘umbrella’ manufacturers, such as Procter & Gamble and General Mills. Clearly there are opportunities for the various brands belonging 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.

Our findings on attenuated advertising response in the presence of competitive interference are sobering for advertisers. Further work can be done to extend our range of categories, but a consistent finding is emerging, namely, that over-advertising is substantially dampening advertising response. Less advertising or smarter media planning is required to reduce this problem.

Table 1a: Descriptive Statistics for the Liquid Laundry Detergents Category

Brand	Mkt Share	Av. Price/¢	Av. Bonus	Av. Price-off	Weeks of advertising	Av. Spots/ week	Av. GRPs/ week	Av. C_{it}
All	11.1	71.4	79.1	3.3	21	3.5	25	147.1
Cheer	5.9	103.1	24.0	4.1	14	2.1	8	154.2
Cheer Free	5.6	104.2	21.9	3.1	7	0.5	2	164.7
Era Plus	8.5	102.9	38.4	0	46	16.8	65	103.2
Solo	11.5	86.9	20.6	3.1	38	15.3	63	105.8
Surf	11.9	97.6	58.2	2.8	29	5.4	36	130.2
Tide	45.5	101.4	138.7	7.7	20	11.2	49	127.1
ALL BRANDS	100.0	95.4	54.3	3.4	26	7.8	36	133.2

Table 1b: Descriptive Statistics for the RTE Cereals Category

Manufacturer/ Brand	Mkt Share	Av. Price/\$	Av. Bonus	Av. Price-off	Weeks of advertising	Av. Spots/ week	Av. GRPs/ week	Av. C_{it}
General Mills								
<i>Cheerios</i>								
-Apple cinnamon	5.5	3.22	7.64	0.00	47	19.7	55.9	136.1
-Cheerios	16.5	3.33	10.91	0.00	49	30.3	87.7	122.6
-Honey nut	11.3	3.26	18.68	2.53	49	28.0	81.4	125.1
Total Corn Flakes	1.5	4.37	0.00	0.00	31	6.3	18.3	154.9
Wheaties	6.9	2.77	15.89	0.00	45	5.8	24.1	148.2
Ralston								
Corn Chex	2.0	3.43	10.43	0.92	6	0.1	0.6	175.9
Double Chex	1.8	2.62	3.34	0.00	4	1.3	10.0	172.0
Rice Chex	2.5	3.42	17.21	0.91	11	1.5	10.2	168.8
Kelloggs								
All Bran	1.9	2.36	0.00	0.00	8	0.2	1.5	174.5
Bran Flakes	2.7	2.32	7.94	0.00	3	0.1	0.1	176.6
Corn Flakes	17.6	1.81	18.85	2.40	37	5.8	18.5	153.7
Crispix	4.2	3.39	3.74	0.02	1	0.0	0.0	178.0
Kenmei	2.4	2.62	3.34	0.00	4	0.1	0.7	176.3
Product 19	2.4	3.64	3.98	0.00	6	0.2	0.7	174.9
Special K	6.8	3.46	5.91	0.49	6	0.1	0.5	175.2
Post Foods								
Grape Nuts	7.9	2.15	5.72	0.00	46	9.3	32.2	145.1
Bran Flakes	2.0	2.35	2.70	0.00	1	0.0	0.2	177.8
Quaker Foods								
Oat Squares	4.1	2.56	11.11	0.00	32	10.2	52.1	141.4
ALL BRANDS	100.0	\$2.95	8.2	0.4	21.4	6.6	21.9	159.8

Table 2: Parameter Estimates for the Sales Response Model for Laundry Detergent

Parameter	Estimate	Standard Error	<i>t</i> -statistic
β_0	10.860	0.109	99.6
$\bar{\beta}_{price}$	-3.374	0.452	-7.5
$\bar{\beta}_{bonus}$	0.031	0.015	2.1
$\bar{\beta}_{priceoff}$	0.115	0.031	3.7
$\bar{\delta}$	-3.341	0.549	-6.1
γ_1	4.929	0.976	5.1
γ_2	-0.982	0.429	-2.3
ρ	0.264	0.048	5.5
σ^2	0.079		
<i>Brand intercepts:</i>			
All	-1.382	0.230	-6.0
Cheer	-1.245	0.121	-10.3
Cheer Free	-1.224	0.122	-10.0
Era Plus	-0.977	0.113	-8.6
Solo	-1.140	0.133	-8.6
Surf	-0.996	0.109	-9.1
Tide	0.000	-	-
Log-likelihood (full model)	-59.9		
Log-likelihood (null model)	-591.0		
DIC	135.2		

Table 3: Parameter Estimates for the Sales Response Model for RTE Cereals

Parameter	Estimate	Standard Error	<i>t</i> -statistic
β_0	10.660	.212	50.3
$\bar{\beta}_{price}$	-2.453	.198	-12.4
$\bar{\beta}_{bonus}$.063	.017	3.7
$\bar{\beta}_{priceoff}$.154	.039	3.9
$\bar{\delta}$	-2.778	.845	-3.3
γ_1	3.384	1.280	2.6
γ_2	-1.003	.418	-2.4
ρ	.218	.028	7.8
σ^2	.068	-	
<i>Brand intercepts:</i>			
Cheerios –Apple Cinnamon	.270	.064	4.2
Cheerios –Cereal	1.100	.081	13.6
Cheerios –Honey Nut	.824	.073	11.3
Total Cereal-Corn	-.129	.089	-1.4
Wheaties Cereal-Regular	.00	-	
Chex Cereals-Corn	-.534	.071	-7.5
Chex Cereals-Double Chex	-1.185	.073	-16.2
Chex Cereals-Rice	-.315	.069	-4.6
Kelloggs-All Bran	-1.117	.076	-14.7
Kelloggs-Bran Flakes	-.885	.073	-12.1
Kelloggs-Corn Flakes	.010	.090	0.1
Kelloggs-Crispix Cereal	.151	.067	2.3
Kelloggs-Kenmei Rice Bran	-.820	.067	-12.2
Kelloggs-Product 19	-.123	.071	-1.7
Kelloggs-Special K	.596	.071	8.4
Post Food-Grape Nuts	-.227	.075	-3.0
Post Food-Natural Bran Flakes	-1.173	.078	-15.0
Quaker Food-Oat Squares Cereal	-.379	.064	-5.9
Log-likelihood (full model)	-86.0		
Log-likelihood (null model)	-1222.2		
DIC	180.6		

Table 4: Optimal number of spot TV GRPs per brand per week when b competing brands advertise at the same GRP level as the focal brand – laundry detergents

b	1	2	3	4	5	6
Optimal GRPs per brand	209	70	38	26	19	15
Optimal total GRPs in category	418	210	152	130	114	105

Figure1: Advertising Elasticity for Increasing Competitive Clutter Levels

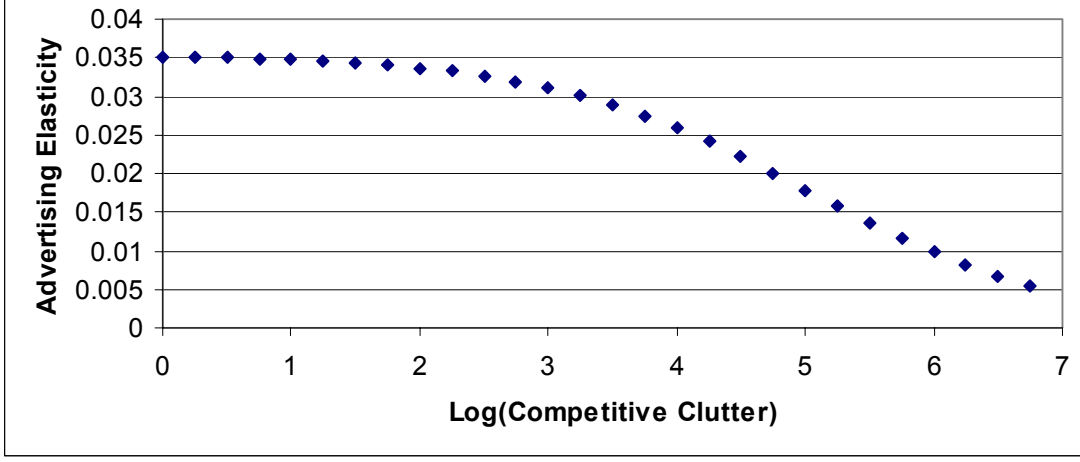


Figure 2a: $\Delta \text{Log}(\text{Sales})$ When Two Brands are Advertising

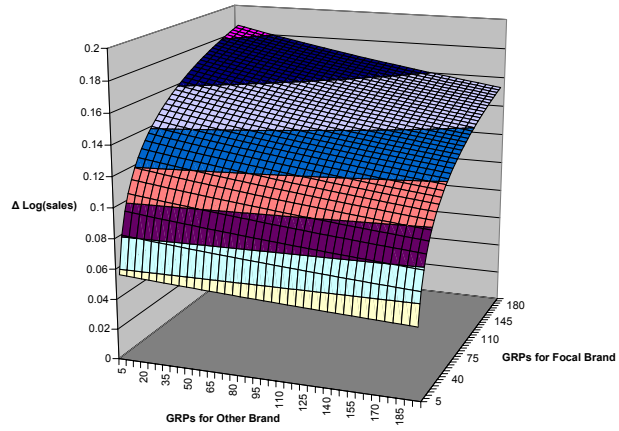


Figure 2b: $\Delta \text{Log}(\text{Sales})$ When Four Brands are Advertising

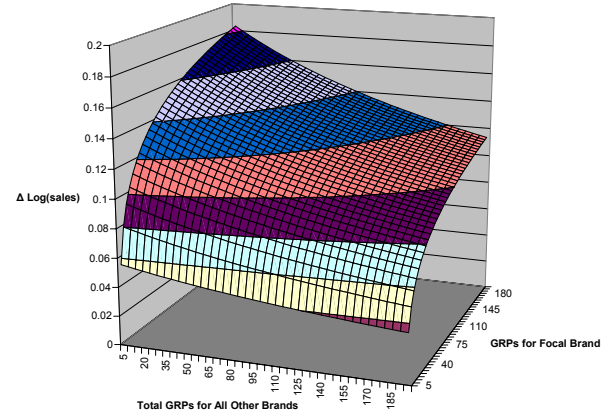


Figure 2c: $\Delta \text{Log}(\text{Sales})$ When Seven Brands are Advertising

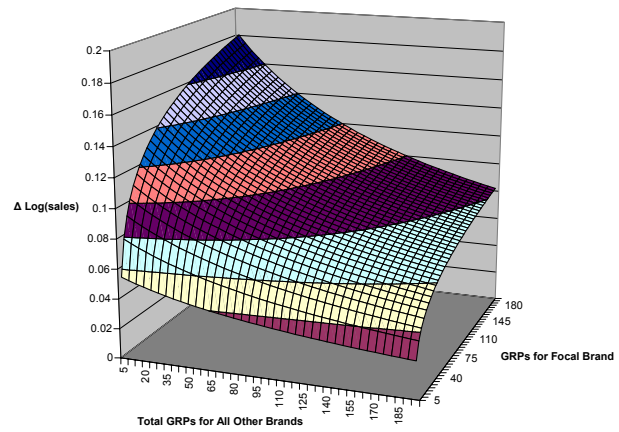
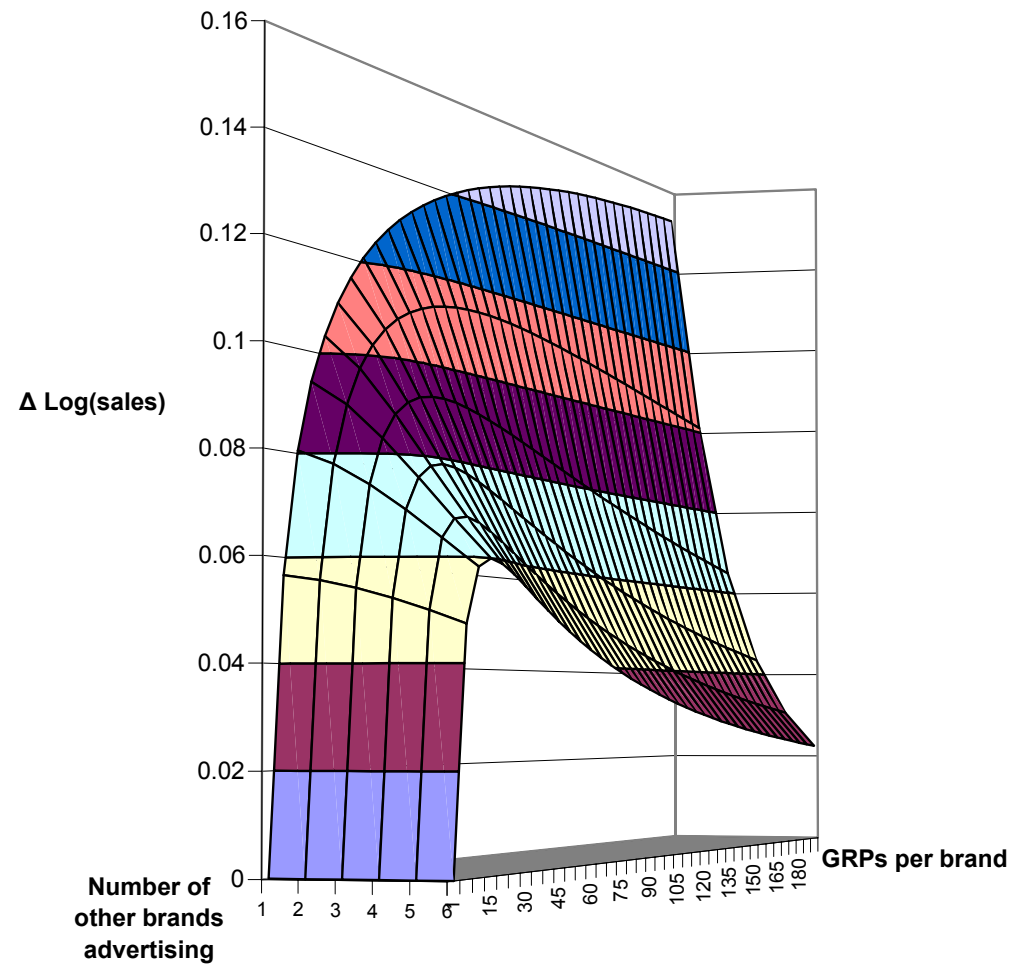
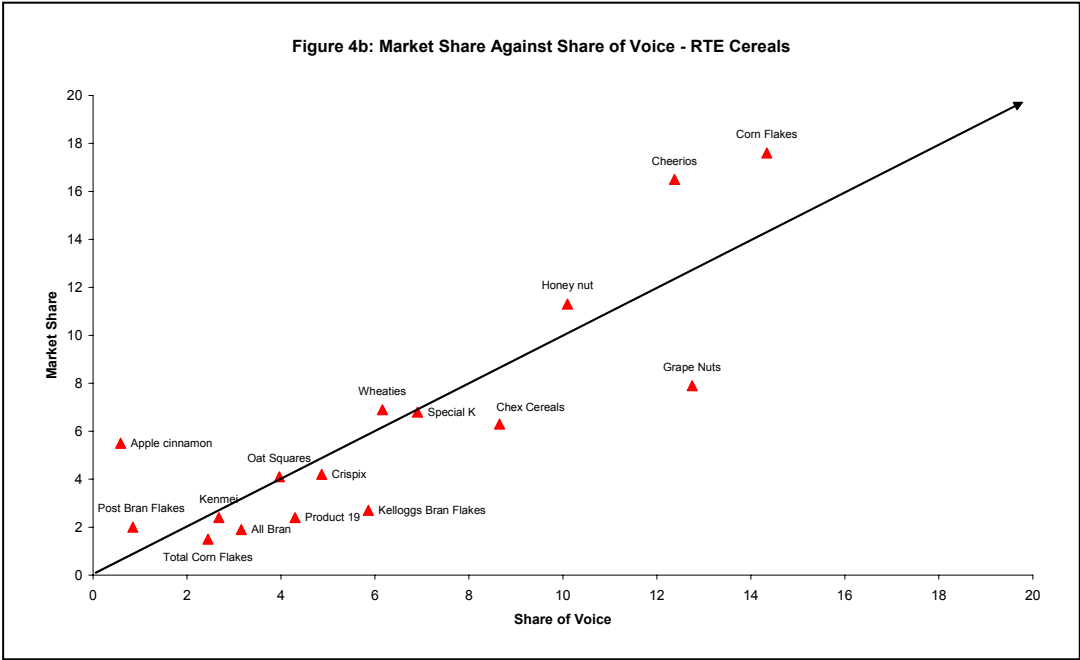
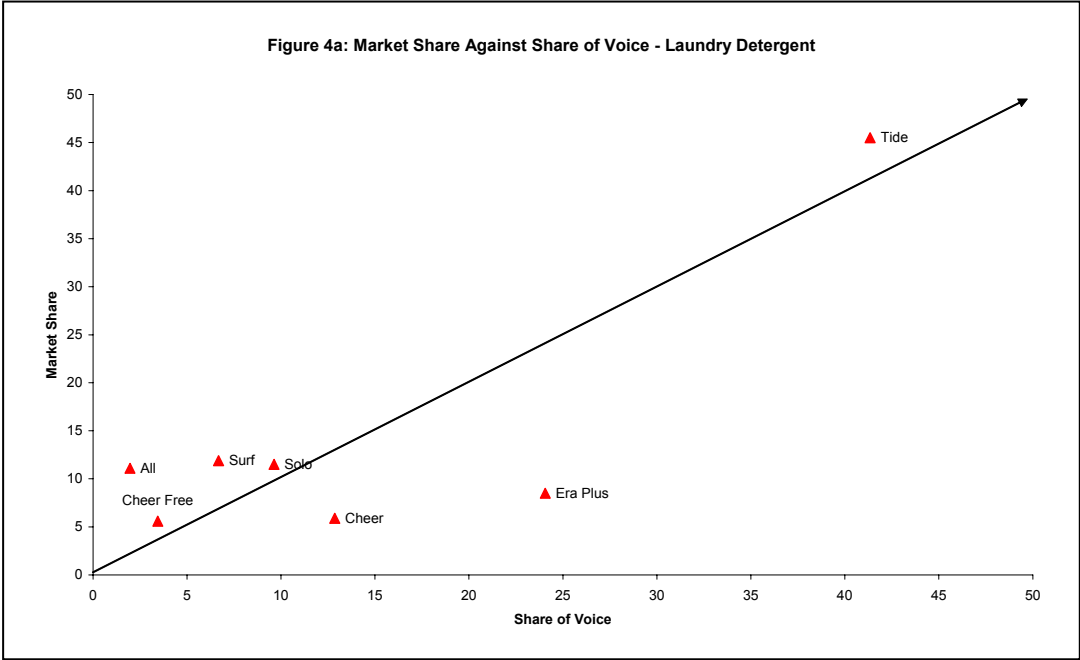


Figure 3: $\Delta \text{Log}(\text{Sales})$ as a Function of GRPs per Brand and Number of Brands Advertising





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