RESEARCH PAPER

Nr. 2, 2004

Long-term Advertising Effects and Optimal Budgeting

by

Professor Flemming Hansen,
ekon. dr.
and
research assistant
Lars Bech Chrisensen, M.Sc.

CENTER FOR MARKETING COMMUNICATION

INSTITUT FOR AFSÆTNING
COPENHAGEN BUSINESS SCHOOL

SOLBJERG PLADS 3, DK-2000 FREDERIKSBERG
TEL: +45 38 15 21 00 FAX NO: +45 38 15 21 01

Long-term Advertising Effects and Optimal Budgeting

Professor *Flemming Hansen*[1], ekon.dr. and
Research Assistant *Lars Bech Christensen*[2], Msc.
Center for Marketing Communication
Department of Marketing
Copenhagen Business School

Abstract: Using pure single-source data, this paper provides evidence for the existence and magnitude of long-term advertising effects across FMCG product categories. Furthermore, we focus on the difficulties that arise for well-established brands when new products are introduced into the market and product innovations take place. Our research shows that such occurrences drastically alter the relationship between share of voice and share of market in any given FMCG market, hence making it pivotal for marketers to focus on such relationships in order to maintain market position.

[1] Contact person:
Professor Flemming Hansen
Center for Marketing Communication
Department of Marketing
Copenhagen Business School
Solbjerg Plads 3
DK-2000 Frederiksberg
Denmark
Phone: +45 3815 2134
Fax: +45 3815 2101
E-mail: fh.marketing@cbs.dk

[2] Co-author:
Lars Bech Christensen, M.Sc.
Center for Marketing Communication
Department of Marketing
Copenhagen Business School
Solbjerg Plads 3
DK-2000 Frederiksberg
Denmark
Phone: +45 3815 2201
Fax: +45 3815 2101
E-mail: lbc.marketing@cbs.dk

Long-term Advertising Effects and Optimal Budgeting

Advertising elasticities

In theoretical economics, the question "what is optimal advertising?" has an elegant answer (Dorfman and Steiner, 1954; Rasmussen, 1957; 1977; Palda, 1969). If we term the price of the product p, the variable costs per unit c, the quantity sold Q and the total advertising spending A, then in the optimal situation, the following condition should be met:

$$E_A = \frac{A}{(p-c)Q} \text{ [2] or } E_A = \text{Advertising budget / Total contribution} \qquad (1)$$

The problems with this simple formulation are first and foremost that:

(I.) It describes a condition that has to be met in the optimal situation, and not a formula that can be applied in any simple, mathematical optimization procedure.

(II.) The problems involved in estimating the advertising elasticity are many and varied, and in the long history of marketing, reliable estimates of advertising elasticities are few.

To estimate 'optimal advertising' as a condition to be met in the optimal situation (I.) disregards some of the real complexities associated with studying advertising effectiveness: In estimating advertising elasticity, one must somehow take into account the dynamic nature of advertising, that is, the short-term, medium-term and long-term effects of advertising spending. This is not easily done. Also, the problem formulation (I) disregards all the dynamic influences of other marketing activities, such as price, product change, distribution etc.

The difficulties in estimating advertising elasticity derive from some of these issues. Particularly in the real world, it is difficult to find data where other factors besides advertising are stable or at least quantified in a meaningful way, so that estimates can be made. Furthermore, it is difficult to define the proper period of time to be studied (month, budget year, other?), and subsequently take into consideration the influence of advertising in previous periods, as well as the influence of the present advertising in future periods. These issues are discussed thoroughly in most marketing texts (Kotler, 1987; Peters and Olsen, 1996); in this particular context, Palda (1969) is an important contributor.

---

[2] E_A – the advertising elasticity – is defined as $\frac{\partial Q}{Q} \Big/ \frac{\partial A}{A}$, where Q is the quantity sold, and A the amount spent on advertising.

Nevertheless, some valuable observations can be made:

1. It can be shown that in the optimal situation, advertising elasticity should be less than one, suggesting that if the data in any way indicate advertising elasticities greater than one, it also suggests under-spending on advertising (Rasmussen, 1957).

2. When the advertising demand function takes on a very special form, namely:

$$q = e^{e_a} , \qquad (2)$$

the advertising elasticity remains constant. In principle, the equations can be solved. This, however, is rarely the case, and certainly never with an *S*-shaped demand function.

3. It follows that for the practical policy of keeping advertising as a fixed percentage of sales to be optimal, this would require advertising elasticity to remain constant over a longer interval.

However, it may be that the advertising demand function in a certain interval around the level of actual advertising spending may be approached with a type (2.) advertising response function. Then if, in the first case, the advertising budget fulfils the conditions proposed in type 1, it would also do so within a certain range of smaller or larger sales quantities with advertising as a fixed percentage of sales.

Short- and medium-term advertising effect and single-source data

In recent years, the access to electronic, single-source data on consumers' exposure to advertising and their purchasing behavior has given the marketer new possibilities of estimating effects of advertising for FMCGs. However, for a number of reasons, these data have rarely been used for calculating advertising elasticities in any direct way (Broadbent, 2001). Rather, more simple measures have been used. Jones (1992) introduces the concept of STAS (Short-term Advertising Strength), defined as

$$\frac{\text{Sales to consumers exposed to ads}}{\text{Sales to all consumers exposed to ads}} \Bigg/ \frac{\text{Sales to consumers not exposed to ads}}{\text{Sales to all consumers not exposed to ads}} \qquad (3)$$

This measure, and its applicability, has been discussed in many contexts (Jones, 1995, 1997; Broadbent, 2001; Hansen and Hansen, 2001). As suggested by its name, *short-term advertising strength* is a measure of the short-term effects of advertising. Other researchers have used different ways of cross tabulating the data – some have looked at the number of days between exposure and subsequent purchase (McDonald, 1997); others have studied sales after exposure one day prior to a purchase, two days prior to a purchase, etc. (Roberts, 1998; McDonald, 1997). Others again have worked with more refined statistical models, such as the logit model (Hansen and Hansen, 2002), or the conditional logistic regression model (Birch, 2002).

In this debate, Jones has put forward an important argument: if no short-term effects of advertising can be identified, then it seems unlikely that any longer term effects can be found (Jones, 2001). Particularly Roberts (1998) and Broadbent (2001) have been concerned with this debate. However, neither of them seems to disconfirm the proposition, and Roberts (1999) even goes so far as to estimate medium-term effects of advertising, assuming a previous short-term effect. He looks not only at the incremental sale created by advertising, studied within an 8-days time interval prior to the purchase event (as it is done in the case of STAS), he also looks at how much additional sales is generated month-by-month within a full year by those consumers who have been exposed to advertising over a period of one month. Here, the short-term effect is the effect observable within the first month following the purchase, whereas the medium-term effect is the effect observed in the following 11 months. Based on data from Taylor Nelson/Sofres' single-source data panel, he finds that the medium-term effect may be 5-6 times as high as the immediate short-term effect. These findings suggest that even modest short-term effects may be profitable, when looked at in this timeframe.

Broadbent (1999) and McDonald (1997) accept this concept, although uncertainties exist regarding the magnitude of the estimates provided by Roberts. Also Knäble (2002) and Battais (2003) provide findings in line with those presented by Roberts. Much more insight into calculations of this kind based on single-source data is needed. However, the proprietary nature of single-source data, and the owner's limited willingness to give researchers access to data at the brand level, makes this difficult. (Beaumont, 2003)

Long-term effects of advertising

Advertising effects are not limited to the sum of short- and medium-term effects. Even longer-term effects may exist, and may be important in their own right for the advertising planning and advertising budgeting. Such effects may be observable in the case of brands where advertising has been terminated, but having been advertised strongly in the past, maintain important market positions. These effects may be thought of as the ability of brands that have been well advertised in the past to obtain premium prices and/or sustain market shares with reduced marketing expenditures. Such effects are particularly observable with brands that have been on the market for an extended period of time. Even though the expectation of such effects may be a major determinant for budget sizes in connection with new introductions, studies attempting to quantify long-term effects tend to concentrate on brands of a longer standing.

Here, the concept of *share of market*, relative to *share of voice* has been an important tool. Underlying all work on share of voice / share of market is the assumption that somehow the share of market, which a particular brand obtains, relates to the brand's share of the total amount of advertising in the product category. However, several issues have to be settled regarding the definitions of share of voice and share of market before meaningful analyses of available data can be carried out.

Share of market may be measured in terms of *share of volume*, *share of purchases,* or *share of units purchased.* As shown by Jones (1989) and Buck (2001), relationships that can be established are not particularly sensitive to the specific choice of share of market measure. More important is the definition of what exactly constitutes the market. In many product areas, competition may exist between brands, normally assigned to different product markets. The fact remains that any given FMCG market consists of a wide variety of very different brands. Buck (2001) shows the average share of market structure for 26 FMCG categories.

Table 1. Average share structure across 26 categories, 1999 (Buck, 2001)

Position in category	**1999 (%)**
Brand leader	32.6
No. 2 brand	14.3
Other brands (each > 2 %)	17.8
Other brands (each < 2 %)	6.8
Private label	28.6
Total	**100**

Over the years, the structure of Buck's data has changed across a number of categories. Since 1975, the market share of private labels has grown from 16.4 % to 28.6 %, resulting in the loss of market shares for all other types of brands in these categories. When studying share of voice versus share of market, very different results emerge, depending upon whether all brands, only brands that are advertised for or all brands except private label brands are included in the study (Jones, 1989; Buck, 2001). The exclusion of private labels may have an important effect in periods where their share of the total market is increasing. In this instance, brands that are advertised are losing market shares, not so as a result of their advertising policy, but rather of the structural changes in the retail market.

The definition of the *share of voice* should be considered thoroughly also. Share of voice may be measured in terms of *share of budget*, and in terms of *share of exposures.* To the extent the different advertisers pay different prices for the same advertising space, the choice of measure becomes important. Moreover, when studies that include a broader variety of media (for instance, both television and print) are carried out, the number of exposures such as GRPs (or TRPs) may not be useful, since they may have different meanings in different media settings.

Major published studies have concentrated on three important relationships.

- *Share of voice vs. share of market*
- *Share of voice minus share of market, relative to share of market*
- *Changes in share of voice vs. changes in share of market*

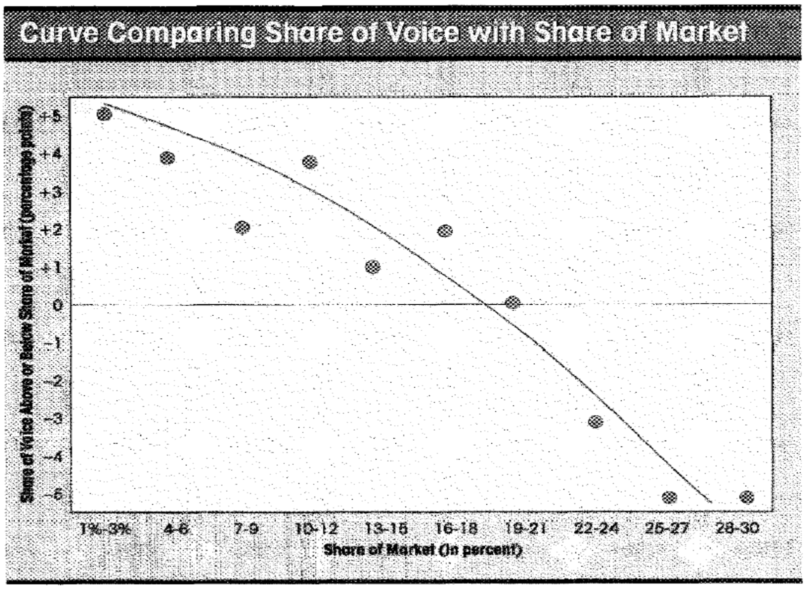
In one of the earliest and most frequently quoted studies, John Philip Jones focuses on the first two measures. Based on data on 1096 international brands, collected by Jones in 1989, and elaborated upon in Broadbent (1989), a relationship appears between share of market (measured as turnover) and share of voice (measured in terms of advertising spending). On average, Jones' data show larger market shares associated with larger shares of voice. In analyzing the data, Jones also introduces the Advertising Intensiveness Curve. The basic data are shown in Table 2. The advertising intensiveness curve based on Jones' data is shown in Figure 1.

Table 2. The advertising intensiveness relationship (Buck, 2001, after Jones, 1992).

Share of Market (SoM) (%)	SoV-SoM (percentage points)
1 - 3	+ 5
4 - 6	+ 4
7 - 9	+ 2
10-12	+ 4
13-15	+ 1
16-18	+ 2
19-21	0
22-24	- 3
25-27	- 5
28-30	- 5

These findings suggest that, on average, larger brands can get away with spending less on advertising, while smaller brands and new brands, trying to get a foothold in the market, have to invest more than average on advertising. A number of individual differences exist for different product categories, and external factors such as the use of promotions, introduction of new brands and heavy retail brand activities influence this basic relationship in the individual markets.

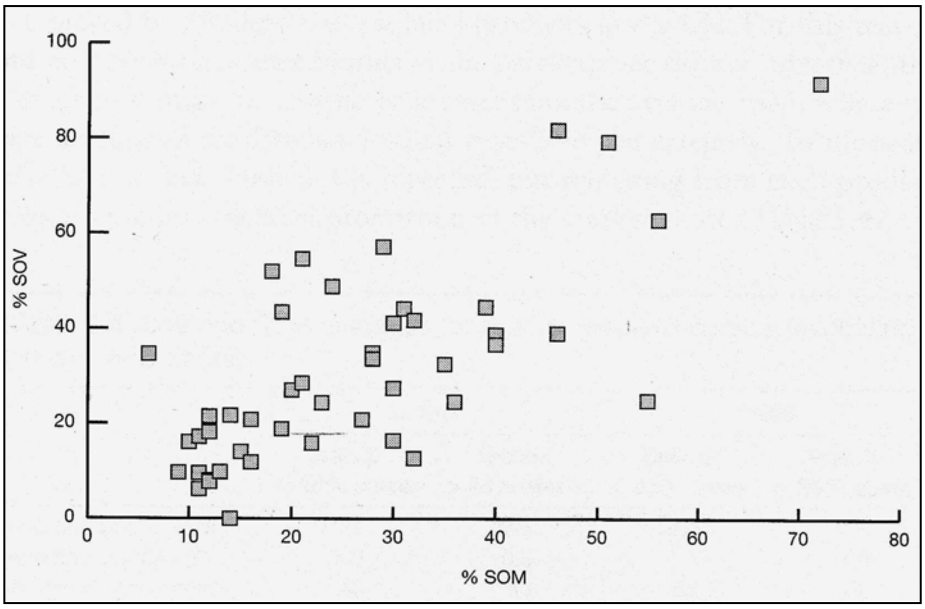
Figure 1. Advertising Intensiveness Curve (John Philip Jones, 1990).



Ill.: J.P. Jones: "Ad Spending: Maintaining Market Share, *Harvard Business Review,* January-February 1990, p. 41.

Another major study is published by Buck (2001). Buck uses Taylor Nelson/ Sofres' Super panel data on market shares, and data on advertising spending from their Market Intelligence data. Here, the share of market is measured in terms of number of purchases, and advertising in terms of gross advertising spending (disregarding individual discounts). Data are collected for individual years, the first being 1975 and the last 1999. In this study, only the first and the second largest brands are looked at within 26 different FMCG categories. The rest of the market is seen as one artificial "third brand". The basic relationship established for 1975 is shown in Figure 2. The 1999 data appear very similar.

Figure 2. SoV vs. SoM 1975. (Buck, 2001)



The existence of an advertising intensiveness curve is also suggested in the data as shown in Table 3.

Table 3. SoV and SoM averages for brands grouped by size (excluding private label shares). (Buck, 2001)

	1975		1999	
	Brands < 28 % share	Brands > 28 % share	Brands < 23 % share	Brands > 23 % share
Average SoV - SoM	+ 2.4	- 2.5	+ 4.3	- 2.5
Average SoV / SoM	1.2	0.9	1.1	1.0
% Investment brands	43	43	55	42

Also, in Buck's data, a relationship between changes in share of market and changes in share of voice is suggested. This is shown in Table 4.

Table 4. SoV vs. SoM related to brand share trends. (Buck, 2001)

	Performance 1995 to 1997	Performance 1997 to 1999
	Average SoV - SoM 1995	Average SoV - SoM 1997
Falling/static brands	3.5	4.7
Rising brands	10.5	14.4

It appears that brands that have been growing during the 4-year period from 1995 to 1999 on average had a larger share of voice - share of market.

In spite of their agreeing results, each of the studies discussed here has its own characteristics. Jones' 1989-data is static in the sense that the relationship between share of voice and share of market is studied in a particular year. Since one may argue that in some cases the relationship results from product managers' decisions to change advertising budgets depending upon how their brand is performing, part of the relationship reported may be ascribable to advertising budgets being adjusted to market share and not vice versa.

The Buck studies rely upon relatively few brands, and therefore it does not enable us to draw complete pictures of the development of advertised brands in individual markets. Also, in all studies, data analyses are carried out at an aggregate level. Total advertising is compared with market share for whole markets. In most published studies, authors have rarely been allowed to identify data on an individual brand level; and to overcome these weaknesses, the present study was developed.

Data for the present study

The AdLab database used here is a diary based single-source panel database, originally developed by Carlton Independent Television, and collected in the UK by Taylor Nelson in the period 1985-1990 (Hansen & Hansen 2001). The panel consisted of app. 1,000 households, and data were collected on a week-to-week basis. Usually, it was the housewife who filled out extensive diaries on FMCG purchases and media usage. The database also comprises brand specific records on advertising in media, and demographic data on the households. Finally, linked to every data reporting is a variable, which states whether or not the specific reporting is valid. In this paper, we use the data on the purchases of brands as an indication of share of market, and we restrict our measure of share of voice to TV ads only, disregarding ads on the radio and in magazines. This is justifiable because an overwhelming part of the spending on advertising in the product categories analyzed here is spent on television ads.

One potential disadvantage with the data that we use is that we cannot say anything about the content of the advertising campaigns of each brand involved. Qualitative data on campaign effects and the content of advertising campaigns used are simply not available to us. Therefore, it is not possible for us to assess why a certain campaign is effective or not. What we can say, however, is whether or not the need to use advertising in order to keep market shares in different markets differs.

Method

The Advertising Intensiveness Curve (AIC).

In order to establish a relationship between share of voice and share of market, first it is necessary to find valid measures for these two shares. We have chosen TV advertising as a measure of share of voice. If we were to investigate other types of brand categories, it would be recommendable to extend the measure of share of voice to include other types of advertising, for instance direct mail, print advertising, etc. As a measure of the extent of the advertising we use the number of broadcast ads for each of the advertised brands.

When using single-source data, the straightforward way to measure market share is to take the actual number of purchases of a particular brand and divide this by the total number of purchases in the product category. This then is the measure of the share of market for the brand. However, this procedure raises some problems, since quite a large number of brands – on average around 60 % in the examined brand categories – do not advertise, which means that their share of voice equals zero, while their share of market is positive. By definition, these brands will always have a negative share of voice (share of voice minus share of market).

The fact that this is the case makes these particular kinds of brands of little or no use to us in the analyses, keeping in mind that we want to examine the relationship between positive shares of voice and positive shares of market. Therefore, we adjusted the data by removing brands that have “no voice” as well as brands that did not have their own brand name in the purchase diary (brands registered as “Other brands” are excluded). Thus, an adjusted share of market is calculated where “the market” now consists of only those brands that have positive shares of voice. Following this necessary adjustment, it was a straightforward task to plot share of market as a function of share of voice, and then apply a regression analysis to establish a best fit of a function to describe the relationship between share of voice and share of market. Similarly, the Advertising Intensiveness Curve (share of voice minus share of market related to the share of market) can be analyzed.

Analysis and results

First, to get a general idea of how the Advertising Intensiveness Curve works and what it says about the relationship between Share of Voice (SoV) and Share of Market (SoM), we will write the formula for the AIC, as we found it in these data:

$$SoV - SoM = \alpha \cdot SoM + Const \qquad \text{(AIC)}$$

From this follows that

$$SoV = (1+\alpha) \cdot SoM + Const$$

When Share of Market changes, either positively or negatively, the resulting change in Share of Voice becomes:

$$\Delta SoV = (1+\alpha) \cdot \Delta SoM$$

where α denotes the slope of the Advertising Intensiveness Curve, as found in the linear regression analyses of the data.

Because α is generally assumed to be negative, we can make a few notes on how the slope of the fitted Advertising Intensiveness Curve influences the need for advertising when share of market is changed. In general, the steeper the slope, i.e. the more negative the α, the less you need to gain shares of voice when you gain shares of market. Correspondingly, the steeper the slope of the Advertising Intensiveness Curve, the less possible it will be to save on shares of voice when you lose market shares.

Our original data from the AdLab database covers 48 different brand categories (for a complete list of categories, see appendix I). Of the total number of 844 brands in the 48 categories, 530 brands or brand constellations were excluded, due to the before mentioned lack of voice or unclear brand definitions. 314 brands were left in 45 categories, representing a total number of purchases of 1,017,798, and a total of 154,784 TV insertions in the period 1986-1989.

Each brands' share of market was calculated, relative to the other advertising brands in the same product category. Figure 3 shows the plot of these 314 brands, and the linear regression best fit of these data.
Table 5 shows the significance and the estimates of the coefficients in the linear regression model. As can be seen, the linear regression model explained 34,7 % of the total variance in the data

Table 5 – Regression analysis for 314 brands in 45 categories.

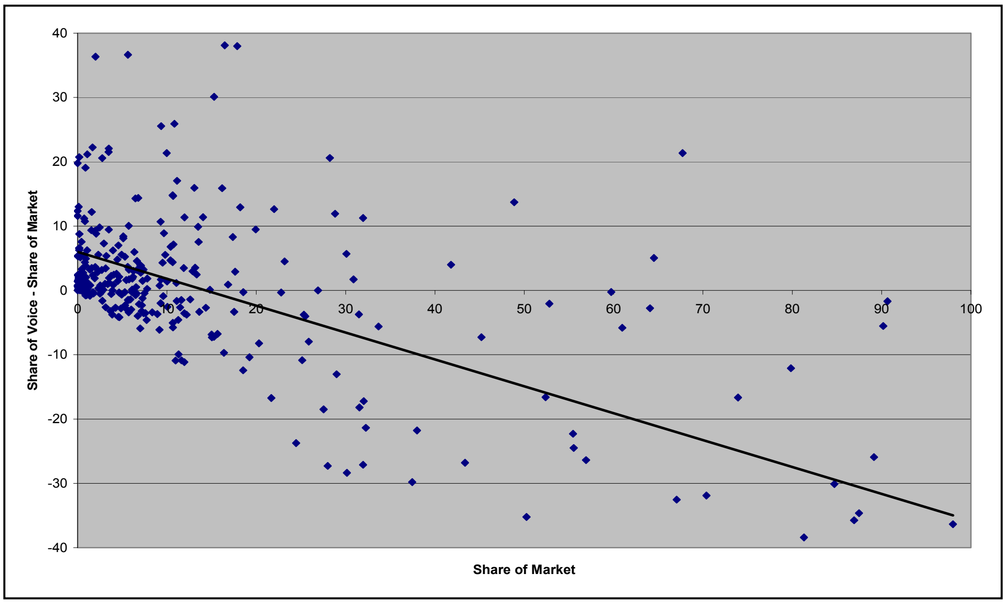
R= .589 *R^2 adjusted = .345* *p<= .000*

		Non-standardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
1	(Constant)	5,991	,826		7,256	,000
	SoM	-,418	,032	-,589	-12,868	,000

Dependent Variable: SoV-SoM

The regression analysis shows that the relationship between share of market and (share of voice-share of market), proposed by John Philip Jones, also exists in these single-source data on FMCG products. On average, brands with smaller market shares evidently keep a share of voice above their share of market, while brands with larger shares of market have relatively smaller shares of voice in general. Furthermore, it shows that on average a brand should keep a share of voice equal to its share of market when its market share is around 14 % of the total market related to advertising brands.

Figure 3. All brands with Share of Voice > 0. Advertising Intensiveness Curve found with linear regression analyses.



The sensitivity of a change in share of market on share of voice can be calculated as

$$\Delta SoM = 1 \Rightarrow \Delta SoV = (1 - 0.418) \cdot 1 = 0.582$$

This indicates that an increase of share of market with 1 percentage point should correspond to an increase in share of voice of 0.582 percentage points in order to keep up with the rest of the market.

At the same time, a decrease in market share of 1 percentage point corresponds to a decrease in share of voice of – 0.582 percentage points.

High voice and low voice product categories.

Our hypothesis was that the level of voice in a certain product category would influence both the slope and the constant of the Advertising Intensiveness Curve. In order to determine what can be said to be a high level of voice, respectively a low level of voice, we therefore applied a separating rule to the data.

Among the 45 examined brand categories, the level of voice varied from category to category – the highest level was found in the "breakfast cereal" category, with a total number of TV advertisements of 24,468 in the 4-year period. At the other end of the scale was the product category "packet soup". In this category, only 146 TV ads were reported in the total 4-year period. The average number of TV ads in the categories was 3,400. We separated the total brand categories into high voice categories – those above 3,400 TV ads – and low voice categories – those below 3,400 TV ads.

Then we applied standard linear regression to the two new datasets – the results are summarized in Tables 6 and 7 below.

Table 6. Regression analysis, high level of voice

$R = .517$ R^2 adjusted $= .263$ $p <= .000$

N = 164		Non-standardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
1	(Constant)	2,585	,568		4,551	,000
	SoM High level of voice	-,303	,039	-,517	-7,686	,000

Dependent Variable: Sov-SoM High level of voice

Table 7. Regression analysis, low level of voice

R = .634 R^2 *adjusted = .398* *p<= .000*

N = 150		Non-standardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
1	(Constant)	10,094	1,643		6,145	,000
	SoM Lav voice cat	-,488	,049	-,634	-9,973	,000

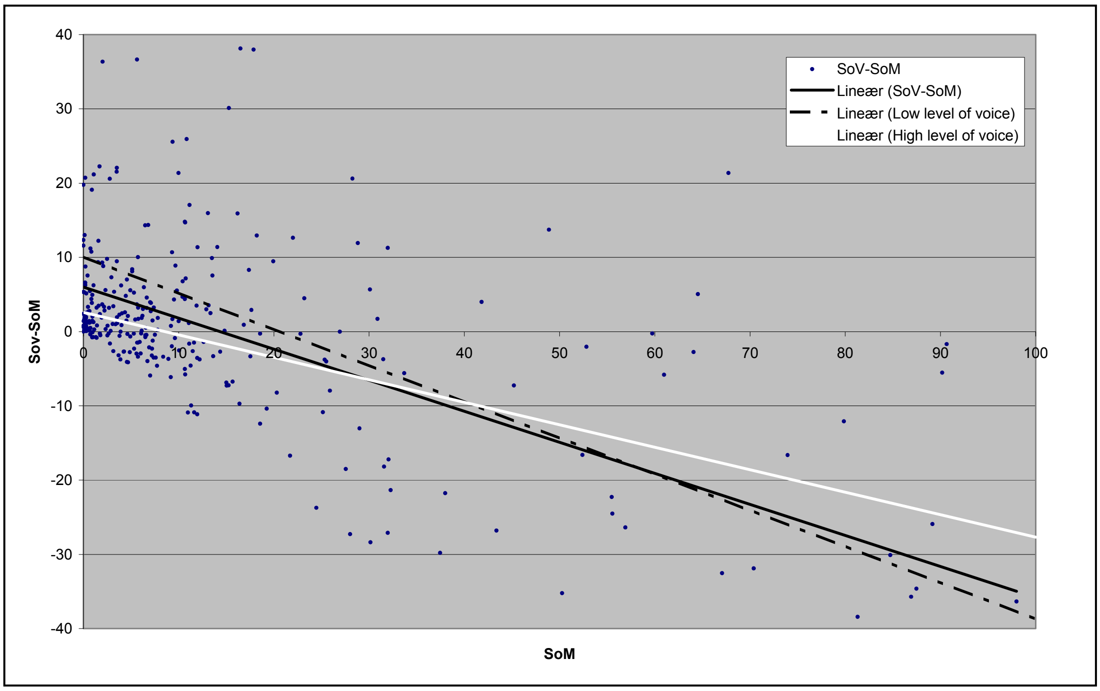
Dependent Variable: Sov-SoM Low level of voice

Both models explain a significant amount of the variance in the data sets. 26,7 % of the variance is explained in the product categories with a high level of voice, while 40,2 % of the variance is explained in the product categories with a relatively low level of voice.

From the coefficients, it can be seen that there are significant differences between the Advertising Intensiveness Curves in the two different types of voice levels. Both the constants, i.e. the intersection of the AIC with the share of voice-share of market axis, and the slopes of the Advertising Intensiveness Curves seem to depend on whether the market has a high or a low level of total voice.

Figure 4 illustrates how high and low voice, respectively, alters the position of the Advertising Intensiveness Curve.

Figure 4. All brands with pos. Share of Voice. Advertising Intensiveness Curves for all brands, high voice, and low voice markets



The black line is the linear regression line representing the best fit of the total data set. The white line represents the best fit of the brands in the categories with a relatively high level of voice, while the dotted black line represents the best fit of the data from the categories with a relatively low level of voice.

As noted earlier, a steeper slope of the Advertising Intensiveness Curve indicates both advantages and disadvantages. In Figure 4, the steepest curve arises among the product categories with a relatively low total advertising budget. The effect of this is that when a brand increases its share of market in a market with low voice, it does not have to increase its share of voice as much as the brand situated in a market with a relatively high voice. In this case, the brand in a low-voice market would have to increase its share of voice with app. 0.51 times the increase in market share – whereas the brand in a high-voice market would need to increase its share of voice with app. 0.70 times the increase in market share. The reason for this could very well be the fact that in a high-voice type of market, it is much more important to follow the norm in the market – when the brand increases in market share, it must also increase its share of voice to a larger extent than in low voice markets.

This seems to imply that brands that operate in high voice markets do not have the same opportunities of making profits from increasing market shares by reducing their advertising budgets as the brands that operate in less voice intensive markets.

On the other hand, the fact that the constant is relatively higher in the analysis of the low voice markets seems to imply that when introducing new brands (which per definition have small market shares) into a low voice market, you need to start up on a higher level of voice than in the high voice market.

Oligopoly and competitive markets

Turning the focus to the type of competition in markets, we set up a rule to separate the data into two different categories of markets, oligopoly and competitive markets. In our analysis, we chose to separate the brand categories in such a way that an almost equal amount of brands fell into the two categories. Our selection rule for the oligopoly category was that the two leading brands combined should hold more than 45 % of the total market, including those brands with no voice. The result of applying this rule was that 27 product categories with a total of 146 brands were classified as oligopoly markets, while the remaining 18 product categories, with a total of 168 brands, were classified as competitive.

Linear regression analyses were carried out on these two new sub-groups of the AdLab database. The result of the analyses is shown in Tables 8 and 9.

Table 8. Regression analysis, Competitive type markets

R = .476 R^2 adjusted = .222   p<= .000

		Non-standardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
1	(Constant)	4,620	1,099		4,203	,000
	SoM comp	-,431	,062	-,476	-6,966	,000

a Dependent Variable: SoV-SoM competition

Table 9. Regression analysis, Oligopoly markets

R = .668 R^2 adjusted = .443   p<= .000

		Non-standardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
1	(Constant)	8,014	1,288		6,222	,000
	SoM oligopoly	-,433	,040	-,668	-10,779	,000

a Dependent Variable: Sov-SoM oligopoly

In this case, both models also explain significant amounts of the variance, 22,6 % and 44,7 %, respectively. Oddly enough, there does not seem to be any significant differences in the slopes of the two models, so the two Advertising Intensiveness Curves can be said to be parallel. The difference between the two market types appears in the *level* of the curves. The Advertising Intensiveness Curve for oligopoly markets lies above the one for competitive markets.

This has some important implications for brands that are situated in oligopoly markets. First of all, when new brands are introduced into an oligopoly market, they need to hold a higher share of voice than new brands introduced into more competitive types of markets. Secondly, smaller brands in oligopoly markets also need to keep relatively higher shares of voice, perhaps forced to do so in order to compete with the dominating market leaders.

The effect of this is underlined by the fact that in oligopoly markets, on average, a brand needs to hold a market share of 18,5 % when share of voice equals share of market, while the same measure for brands situated in competitive markets is 10,7 %.

Share of voice and share of market in individual markets

To carry out more detailed analyses on how individual categories have developed, and particularly to focus on related changes in share of voice and share of market, it was necessary to concentrate on markets with at least three advertised brands and on markets where the total share of market held by the adverted brands was relatively stabile in the period of analyses. Particularly, this last issue implied that markets with penetrating retailer brands should be excluded from the analyses. Based upon these criteria, the following analysis was carried out on 34 product categories, covering approximately 314 brands.

Of the 34 markets, 29 markets showed a clear, positive correlation between share of voice and share of market. Among these, 26 had an advertising intensiveness curve with a negative slope. Of the 29 markets, where data for more than one year exist, 15 markets showed a more or less positive correlation between changes in share of voice and changes in share of market.

Results

Breakfast cereals

The first category that we analyzed was the breakfast cereal category, where data exist on the purchasing of and advertising for 26 brands over a 4-year period. One single producer of different kinds of cereals, the Kellogg Company, heavily dominates the category. This producer alone holds a total market share of more than 60 % in the UK market. The dominating brand is *Kellogg's Cornflakes*, with a market share in 1986 of around 24 %. The second largest brand, measured on market share, is *Weetabix,* produced by the leading British producer of breakfast cereals, Weetabix Ltd. At the beginning of the 4-year period, this brand holds a share of market of around 19 %.

An analysis of the data showed that both leading brands under-spent on advertising every year in the 4-year period. This is illustrated in Figure 5. This is possible, because in the past both the Kellogg Company and Weetabix have invested heavily in building strong brands in the market, and now this investment is paying off. Whereas smaller brands in the breakfast cereal category are forced to advertise more than their share of market would suggest, these large established brands are able to sustain their dominating positions in the market with a relatively small investment in advertising.

Our analysis of the Kellogg Company portfolio of brands showed that, in the 4-year period, a number of new brands from this producer were introduced into the market. In order to get a foothold in the market, the producer was forced to uphold a large advertising spending relative to the share of market of these brands. This overspending on advertising both in 1988 and 1989 is shown in Figure 6. The overall result for the producer is an increase in total market share, from 64.2 % in 1986 to 66.6 % in 1989. At the same time, an increase in share of advertising can be found. In 1986, the Kellogg share of total TV advertising in the breakfast cereal category was 73 %. This compares to 77.5 % in 1989.

Figure 5. Breakfast cereals. Under-spending on advertising for leading brands.

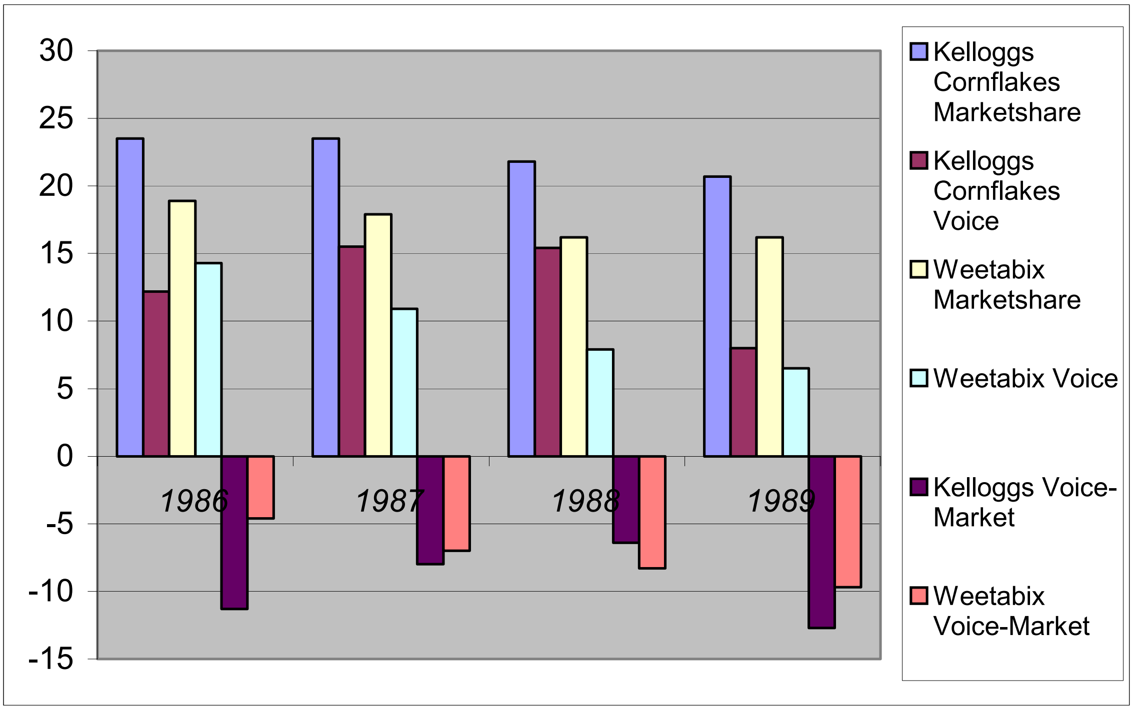
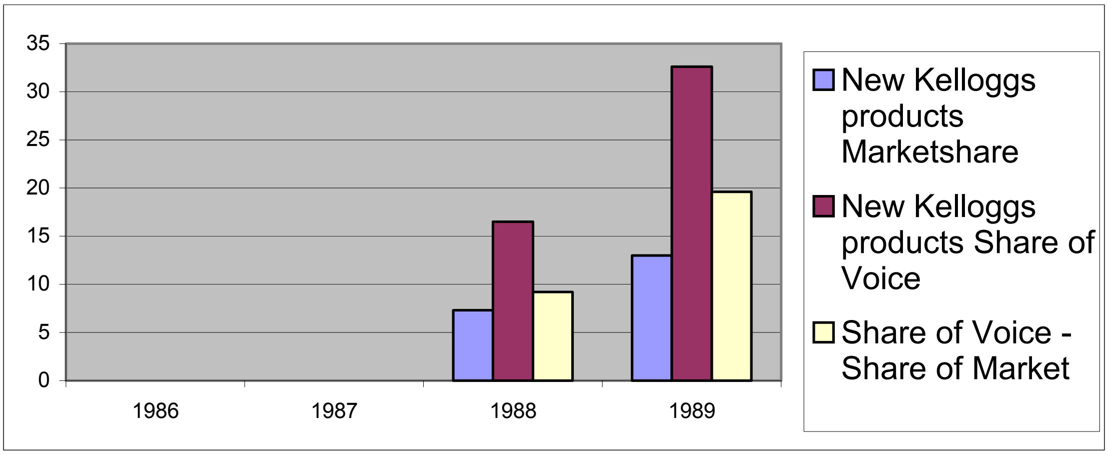


Figure 6. Breakfast cereals. Overspending on advertising for new Kellogg brands.



Overall, although the Kellogg company was spending more on advertising in the 4-years, relative to the total share of market of the Kellogg brands, large differences exist between brands, and our analysis suggests that the larger, established brands of the company are in a sense paying for the introduction of new brands into the market, simply by being able to sustain significant, large market shares with relatively small advertising budgets. By redirecting advertising spending to new products, the Kellogg Company is able to broaden the market and the customer base, maintaining market position of the leading brands, without significantly increasing the total spending on advertising.

The complete picture of the breakfast cereal category is shown in Figure 7. The figure shows the Advertising Intensiveness Curve for the category, and supports the theory that smaller brands need to overspend on advertising, while larger, well-established brands can afford to under-spend while still maintaining their dominating positions in the market.

Figure 7. Advertising Intensiveness Curve, breakfast cereals.

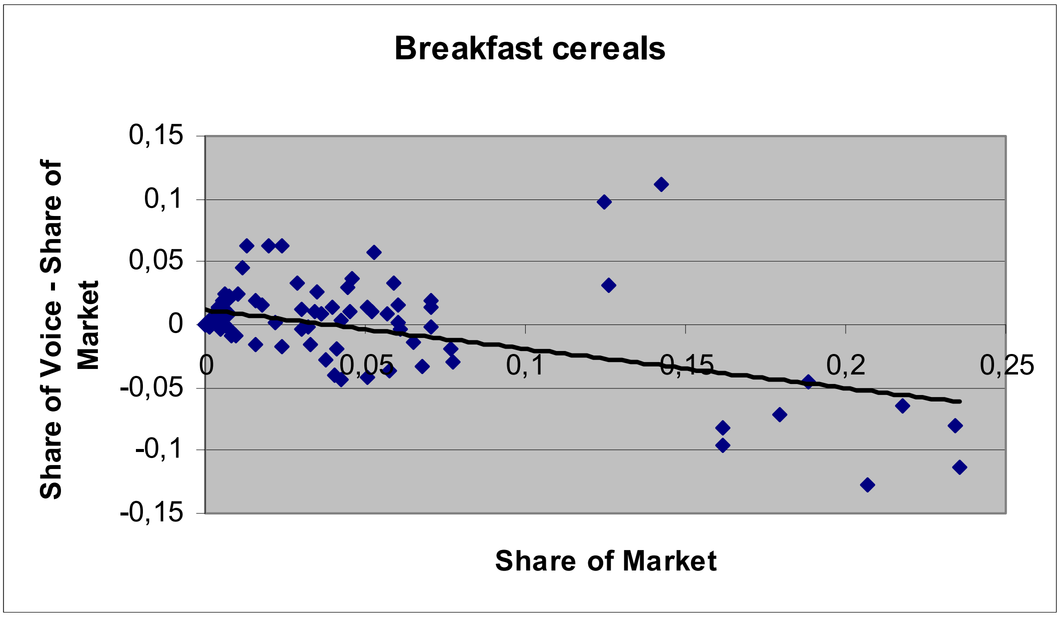
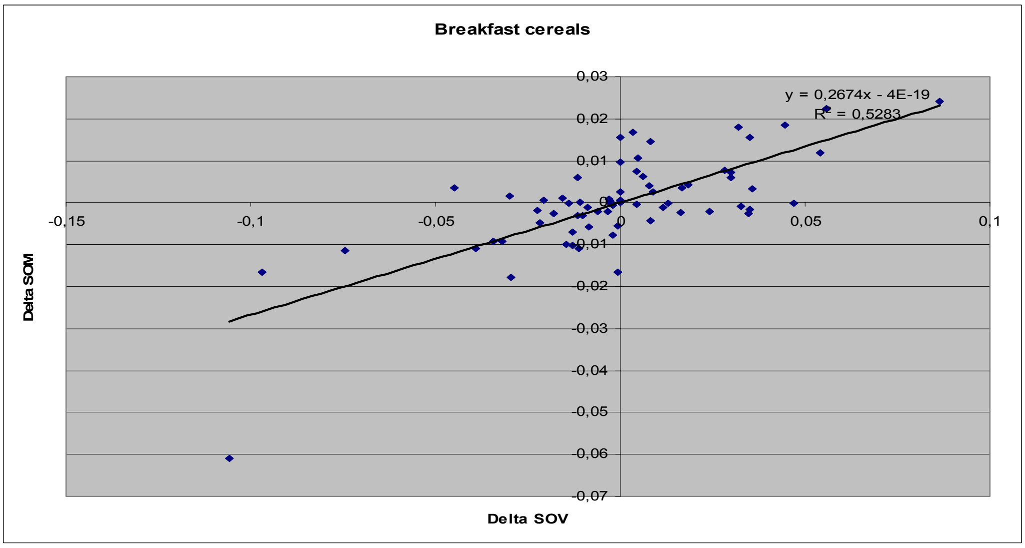


Figure 8 shows that advertising in general seems to work in the product category. The positive relationship between changes in share of voice and share of market indicates that an increase in the spending on advertising, relative to total advertising spending in the product category, will in general lead to a fractional increase of market share.

Figure 8.Changes in share of voice and share of market, breakfast cereals.

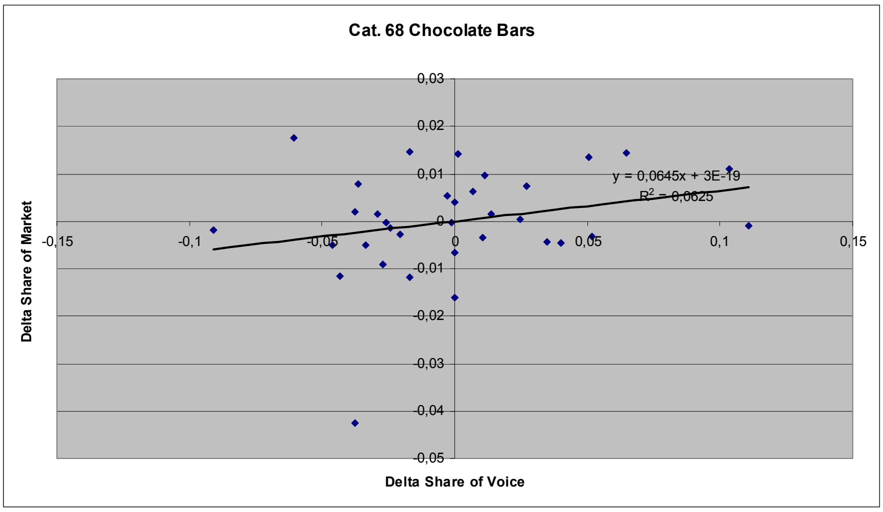


Chocolate bars

The same picture of a positive relationship between changes in share of voice and share of market can be found in the data on a number of other product categories. Although the magnitude of advertising effectiveness varies from category to category, they all seem to indicate that on some level advertising works.

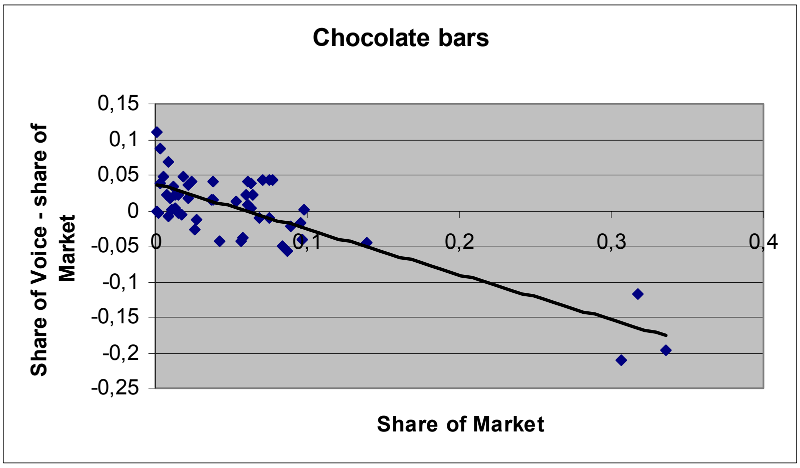
The chocolate bar category is dominated by one large brand, *Mars*, which holds an around 30 % market share. An analysis of data from a 3-year period, depicted in Figure 9, shows the positive relationship between changes in share of voice and share of market, but as it appears, the relationship is not as clear as in the breakfast cereal category.

Figure 9. Chocolate bars. Changes in share of voice and share of market.



Again, the Advertising Intensiveness Curve drawn from data in this particular category shows that, in general, smaller brands need to overspend on advertising in order to maintain their market shares, while larger brands (in this category particularly *Mars*) can profit from being large, and maintain their leading position in the market while, relatively speaking, under-spending on advertising.

Figure 10. Advertising Intensiveness Curve, chocolate bar category.



Automatic washing powder

Another example is found in the automatic washing powder category. In this case, the positive connection between changes in share of voice and share of market seems clearer than in previous examples, indicated by the steepness of the tendency line, see Figure 11.

Again, the category is dominated by one large brand, *Persil Automatic*, which holds around 30 % of the market. There is some indication of this brand under-spending too much during the 4-year period, since it loses significant market shares from 1986 to 1989, see Figure 12.

Figure 11. Changes in share of voice and share of market, automatic washing powder.

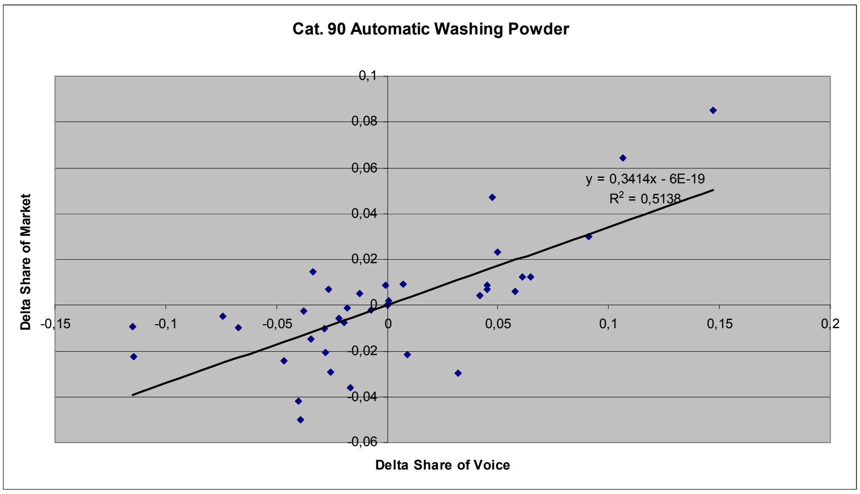
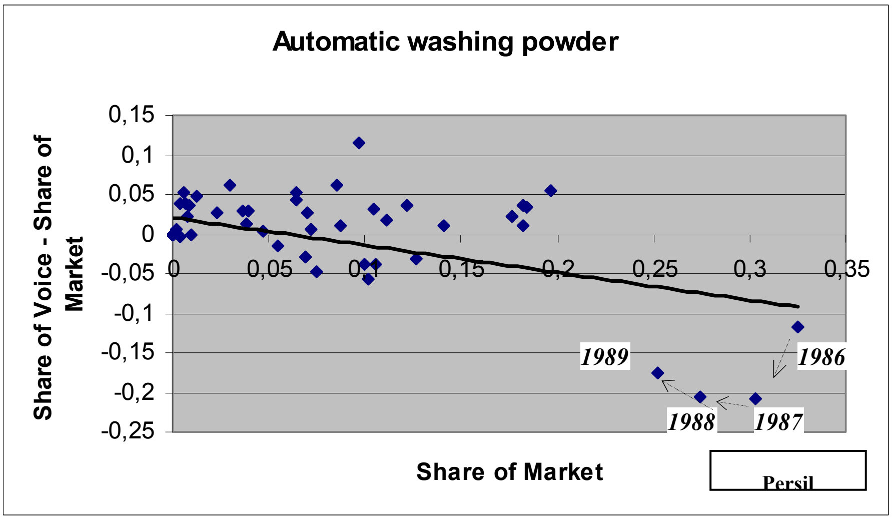


Figure 12. Advertising Intensiveness Curve, automatic washing powder.



This category gives an example of the fact that it is important to get an accurate estimate of how much it is possible for a producer to under-spend without losing market shares. The measure is in a sense a dynamic one, since the introduction of new products may drastically alter the competitive situation in any given market over a relatively short period of time, and at best render previous estimates inaccurate; at worst completely worthless.

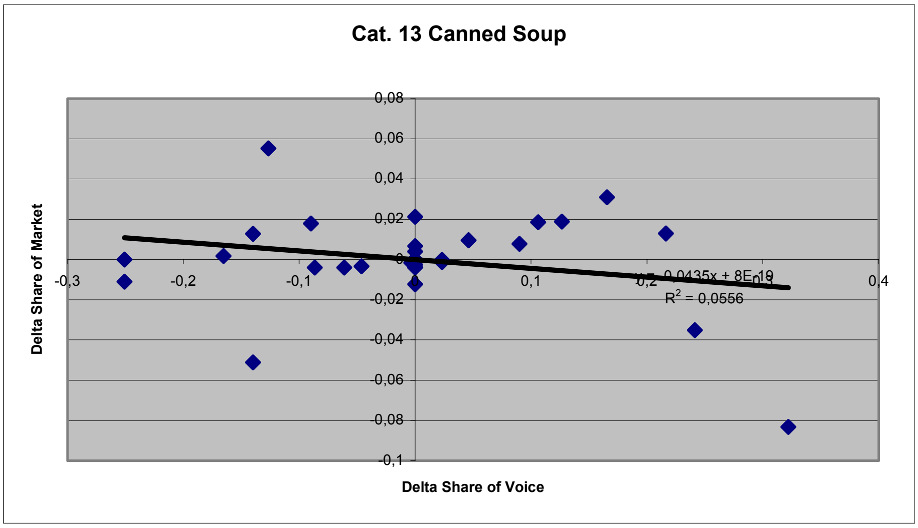
The next category analyzed is an example of this.

Canned soup

Figure 13 shows the relationship between changes in share of voice and share of market in the canned soup product category. The relationship is a different one in this category as can be seen by the negative slope of the tendency curve. This would indicate that, in general, increasing the relative share of advertising for a brand in this category will lead to a loss of market share for that particular brand. However, the explanation for this seemingly negative relationship lies in the development of the market in the years analyzed.

At the beginning of the period, the brand *Heinz Standard* held a market share of nearly 90 %, and was therefore completely dominating this particular product category.

Figure 13. Changes in share of voice and share of market, canned soup category.



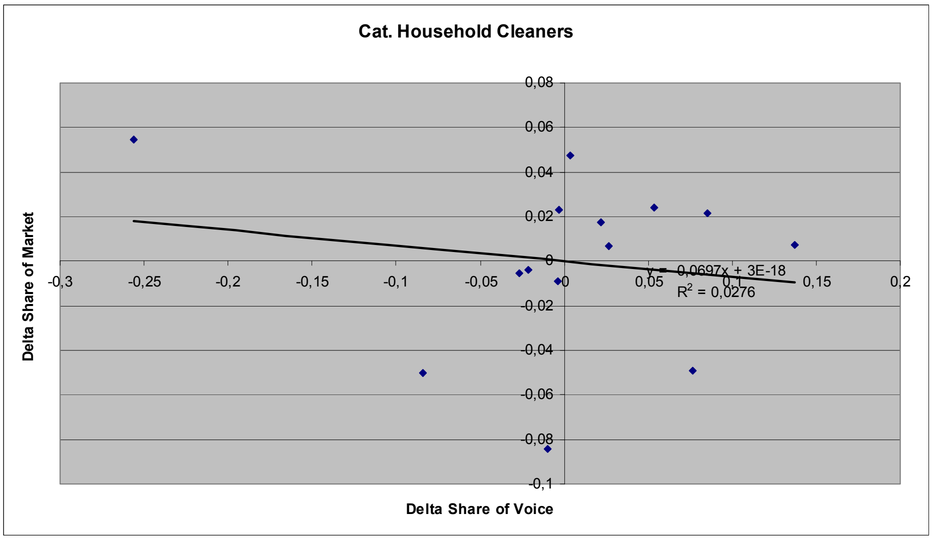
Then, Heinz decided that it was time to innovate the category, and introduced a number of more specified brands with particular tastes, appealing to particular target audiences. These new products were heavily advertised for a short period of time, but as they quickly became popular and gained significant market shares, advertising for these new products almost seized. Still, they continued to grow in market share. This resulted in the leading brand, *Heinz Standard,* losing market shares, even though Heinz continued to advertise their leading brand to the consumers. This is the explanation for the negative relationship between changes in share of voice and share of market, which can be observed in Figure 13.

The lesson to be learned from this is that although in most cases there seems to be a positive relationship between changes in share of voice and share of market over time, some markets may show different, market-specific patterns of behavior.

Household cleaners

This product category gives yet another example of how product innovation in a particular market can significantly alter the relationship between changes in share of voice and share of market, see Figure 14.

Figure 14. Changes in share of voice and share of market, household cleaners.



In the period of time covered by the data, a significant change from powder cleaning products to liquid cleaners occurred in the UK. The fast growing popularity of this new, innovative line of products resulted in liquid cleaners increasing in market shares faster than their share of voice increased. At the same time, advertising for the leading powder cleaner was almost doubled, and still it lost almost a third of its market share, not being able to advertise its way out of trouble.

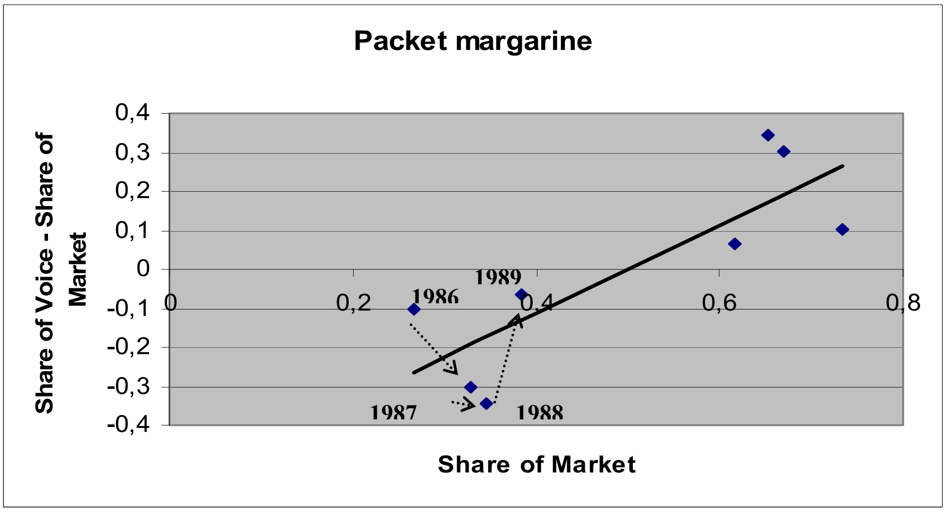
A change in product types and successful innovations can alter the relationship between changes in share of voice and share of market, and seemingly render advertising useless for brands under pressure.

The effect of truly great advertising

Finally, in analyzing the data, we found an example of how great advertising can influence the Advertising Intensiveness Curve in a product category. In the product category packet margarine, only two products where advertised, *Stork* and *Krona.*

In the mid 1980s, *Stork* was very successfully promoted with a long running and award-winning advertising campaign, the result of which can be seen in Figure 15. Although the smaller of the two leading brands, *Stork* was still able to cash in on a very successful, prize-winning advertising campaign, by under-spending on advertising, and still raise the market share from 26.6 % in 1986 to 38.4 % in 1989. The question then is, would it have been possible for *Stork* to achieve an even better market share with more advertising?

Figure 15. Advertising Intensiveness Curve, packet margarine.



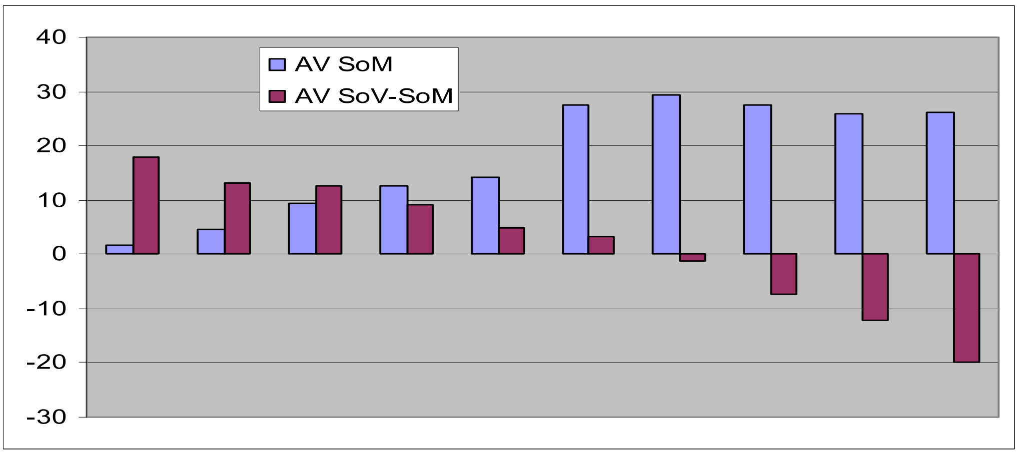
Conclusion

Although there are vast differences across product categories, larger brands generally tend to have the ability to under-spend on advertising without the loss of market power and dominance, see Figure 16.

Still, as several examples have shown, larger brands cannot under-spend too much without being punished on market share. Since this measure is a dynamic one, constant analyses of the market are needed to insure that the amount of advertising invested in the brand is the correct one in relation to the role the brand is supposed to play in the market.

Innovations in the market place and extremely successful advertising campaigns for competitive brands distort the Advertising Intensiveness Curve, and thereby distort the measures needed to sustain a brands position in the market. Therefore, attention must also be directed towards such issues when decisions are being made for investments in advertising.

Figure 16. Average share of voice-share of market in %-points, related to the average market share of the brand (300+ brands in 34 categories of FMCG products).



References:

Battais, Laurent, 2003. Key learnings on advertising effects in FMCG from France and Germany. Presentation at the 2003 European Advertising Effectiveness Symposium, Frankfurt, June 2003.

Beaumont, 2003. Effective frequency – does one size fit all?, Synopsis for the 2003 European Effective Communications Symposium, Frankfurt, June 2003.

Birch, Kristina, 2002. Analyzing Effects of Advertising Using Conditional Logistic Regression. In: *Branding and Advertising,* Flemming Hansen and Lars Bech Christensen (eds.). CBS Press, Copenhagen, 2003.

Broadbent, Simon, 1989. The Advertising Budget, NTC Publications Ltd, 1989

Broadbent, Simon, 2000. Advertising Budgeting. World Advertising Research Centre, London, 2000.

Broadbent, Simon, 1999. When to Advertise. Admap Publications, Henley-on-Thames, 1999.

Buck, Stephan, 2001. Advertising and the Long-term Success of the Premium Brand, World Advertising Research Center, 2001.

Dorfman, R. & Steiner, P.O., 1954. Optimal advertising and optimal quality. American Economic Review, December 1954.

Hansen, Flemming, Lars Grønholdt and Lotte Yssing Hansen, 2001. Modelling Purchases as a Function of Advertising. International Journal of Advertising, Vol 21(1), 2002.

Hansen, Flemming, Lars Grønholdt and Lotte Yssing Hansen, 2002. STAS and Logit Modelling of Advertising and Promotion Effects. Research Paper, Center for Marketing Communication, Copenhagen Business School, 2002.

Jones, J. P., 1989. Does it pay to advertise?, Lexington Books, 1989.

Jones, J. P., 1992. How much is enough?, Maxwell Macmillan International, 1992

Jones, J. P., 1995. When ads work: New proof that advertising triggers sales. New York: Lexington Books/The Free Press, 1995.

Jones, J. P., 1997. What does effective frequency mean. Journal of Advertising Research, Vol 37(4), 1997.

Jones, J.P. 1999. How to Use Advertising to Build Strong Brands, Sage Publications, 1999.

Jones, John Philip, 2002. The Ultimate Secrets of Advertising, Sage Publications, 2002.

Knäble, S., 2002. Ensuring the maximum short-term benefit from television advertising investment. Presentation given at the 2002 European Advertising Effectiveness Symposium, Amsterdam, June 2002.

Kotler, P. and Armstrong, G., 1987. Marketing – an introduction. Prentice Hall, 1987.

McDonald, Colin, 1997. From frequency to continuity – is it a new dawn?, Journal of Advertising Research, Vol 37(4), 1997.

Palda, K.S., 1969. Economic Analysis for Marketing Decisions. Englewood Cliffs, N.J.Prentice Hall Inc., 1969.

Peters, L. & Olsen, J., 1996. Marketing, Prentice Hall, 1996.

Rasmussen, A., 1957 and 1977 (1st and 2nd editions). Pristeori eller parameterteori. Nyt Nordisk Forlag – Arnold Busck. København, 1977 (2nd edition).

Roberts, Andrew, 1997. Optimising Advertising and Promotions. Paper given at the 1997 European Advertising Effectiveness Symposium, 1997.

Roberts, Andrew, 1998. Linking Sales to Advertising Activity. Admap, The Advertising Association, January, QEII Conference Centre, London, 1998.