# Asymmetric Advertising Response

## Abstract

Companies under pressure from stakeholders to meet profit expectations are often tempted to cut advertising expenses, particularly in times of economic difficulties. However, firms may not fully grasp the actual impact of such drastic cuts. Indeed, the general assumption is that advertising effects are symmetric: the numerical sales impact of budget increase or decrease would be the same in absolute value. Our paper addresses this gap by developing a new model based on multivariate time-series analysis (VAR models) to capture these asymmetric dynamic relationships. Our results show that advertising models are improved by allowing the capture of these asymmetric patterns.

**Key-words**: *advertising, asymmetry, time-series, Vector Auto-Regressive models*

**Track**: Advertising, Promotion, and Marketing Communications

Advertising budget decisions made by firms may be subject to revisions and cuts according to sales and profit progress, particularly in times of economic crisis (Kotler and Caslione 2009).  MacLeod (2009) shows that the current financial crisis led to a fall in advertising spending in 2008, and provides more drastic negative forecasts for 2009. Firms as well as researchers may not have a precise idea of the actual impact on sales of these drastic advertising cuts. The impact of a decrease in advertising is either not considered or treated with the underlying assumption that this impact is symmetric. However, even if the issue of advertising asymmetry has been overlooked in marketing research, the few studies interested in this question seem to show that the symmetry assumption is incorrect (Little 1979; Simon 1982; Pauwels et al. 2004a). Consequently, the objective of our research is to propose a dynamic model enabling the taking into account of asymmetry in advertising effects in order to perform more accurate forecasts.

## 1. Asymmetric Advertising Response

### 1.1. Increases and decreases in advertising

The quantification of the impact of marketing variables on sales is fundamental for marketers, since they have to precisely justify their expenditure in order to keep their credibility (Rust et al., 2004). In this aim, numerous models attempt to link advertising expenditure with sales levels (for a review, see Vakratsas and Ambler 1999). However, existing models exclusively study the impact on sales of an increase in advertising. (MacInnis et al. 2002). They do not investigate the negative impact of an advertising decrease.

The scarcity of models dealing with advertising decrease is all the more surprising given that the issue of advertising expenditure cutbacks is very often a major concern in managerial reviews (Aspan 2009). Reasons explaining these cutbacks are numerous. First, advertising cuts may be decided during the year, when managers have to revise their sales or profit forecast (Batra et al. 1995). Second, advertising cuts are sometimes due to legal reasons such as advertising limitations or even bans on specific products (Robert 2007). Third, advertising decreases may result from consideration of advertising alongside other marketing activities which may be considered to be preferable or more efficient (Thietard and Vivas 1984).

### 1.2. Asymmetry in advertising models

One of the first researchers to examine advertising asymmetry was Little (1979) in his review of aggregate advertising models. He shows that sales responses due to advertising increase and decrease are very different. In case of an increase in advertising, there is a quick rise in sales up to a peak (wear-in) followed by a decline (wearout) until an equilibrium level is reached, situated between the original level and the peak. In case of a decrease in advertising, sales decay takes place more slowly than sales progression following an advertising increase and lasts over time (with no equivalent to the wearout effect).  Little (1979) gives an explanation of this pattern. When exposed to an advertising wave (about three exposures), consumers have the product in mind and can therefore quickly make a decision to buy the product; conversely, when advertising decreases, consumers still have an experience with the product (functional by using it, and even emotional by liking it), which explains that it takes a much longer time to forget it even in the absence of advertising.

Other research starts from these observations in order to answer specific research questions. Simon (1982) also deals with advertising asymmetry issues and builds on Little's observations to design optimum advertising strategies and shows that pulsation strategy is the most efficient. Vande Kamp and Kaiser (1999) show that sales response in the milk market are not reversible, meaning that it is not possible to apply a symmetric response rate for the impact of an increase and a decrease of advertising on sales. In concordance with previous results, they find that consumers answer more quickly to increases in advertising compared to decreases.

Based on these elements, we develop our main hypothesis:

H1: An asymmetric time-series model better explains market dynamics, leading to a better goodness of fit than a symmetric model

## 2. Research Methodology

Pauwels et al. (2004b) point out that an adequate model linking advertising and sales must provide four main characteristics. First, the model should be able to provide for the flexible treatment of short-term and long-term impact of advertising on sales. Second, the model has to be robust to deviations from stationarity. Third, the model must provide an expected baseline for the sales series: this would allow measuring the impact of unexpected changes in the advertising budget. Fourth, the model should allow for various dynamic feedback loops of advertising performance. Fifth, a model should take competition into account. We add a sixth requirement by claiming that an adequate model should be flexible to the asymmetric impact of advertising on sales (Little 1979; Pauwels et al. 2004a).

### 2.1. A benchmark model: VAR (Vector Auto-Regressive) model

An interesting first step to building a model meeting all these requirements is provided by vector auto-regressive (VAR) models (Dekimpe and Hanssens 1995, 1999). VAR models are extensively used in marketing research since they are suitable for "*measuring the dynamic performance response and interactions between performance and marketing variables*" (Pauwels et al. 2004a, p.144). Representative studies using VAR models are thus numerous (Pauwels and Srinivasan 2004; Srinivasan et al. 2009).

A standard specification of the VAR model measuring the impact of advertising expenditures on sales performance is given by the equation (1) below:

$$
\begin{bmatrix} MS_t \\ SOV_t \end{bmatrix} = \begin{bmatrix} a_{0,MS} & \delta_{MS}t \\ a_{0,SOV} & \delta_{SOV}t \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} \beta_{11}^i & \beta_{12}^i \\ \beta_{21}^i & \beta_{22}^i \end{bmatrix} \begin{bmatrix} MS_{t-i} \\ SOV_{t-i} \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} \gamma_{11}^i & \gamma_{12}^i & \gamma_{13}^i & \gamma_{14}^i \\ \gamma_{21}^i & \gamma_{22}^i & \gamma_{23}^i & \gamma_{24}^i \end{bmatrix} \begin{bmatrix} PR_{t-i} \\ REB_{t-i} \\ CPR_{t-i} \\ CREB_{t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{MS,t} \\ \varepsilon_{SOV,t} \end{bmatrix} \quad (1)
$$

In this system of equations, $MS_t$ represents the market shares of the focal brand at time t. $SOV_t$ represents the share of voice of the focal brand at time t. Both of these variables are endogenous. Some exogenous variables allow control for factors that could also impact on both endogenous variables: $PR_t$ and $REB_t$ represent the price and the rebate of the studied brand at time t, and $CPR_t$ and $CREB_t$ represent the price and the rebate provided by competitors at time t.

Such a VAR model satisfies the first five requirements we specified above. However, by construction, this VAR model is symmetric regarding the impact of advertising on sales. Indeed,

as the impact of past values of share of voice (SOV) on market share (MS) is represented by a unique coefficient $\beta_{12}$, a positive one unit increase in past SOV would lead to an increase by $\beta_{12}$ of MS, and a one unit decrease in past SOV would lead to a decrease by $\beta_{12}$ of MS. Similarly, a positive unexpected unit shock will generate an impulse response function for MS based on the coefficient $\varepsilon_{SOV,t}$, and a negative unexpected unit shock will generate an impulse response function for MS based on the coefficient $-\varepsilon_{SOV,t}$.

## 2.2. An asymmetric model

Our objective is to start from this benchmark VAR model in order to keep all its fundamental advantages regarding the first five requirements that we listed above and to make it meet the sixth one. Thus, we propose a new way of specifying this standard time-series model such that asymmetry is included in the measure of the impact of the independent variable of interest (i.e. share of voice).

In the VAR model, positive and negative impacts of SOV on MS are by construction, symmetric. In order to allow positive and negative impacts to be asymmetric, we propose to breakdown the independent variable of interest (i.e. SOV) into two sub-variables, one series capturing the increases in SOV and one series capturing the decreases in SOV. Each series would then be linked to the dependant variable of interest (i.e. MS) by a different coefficient.

At the first period, all three series are equal, as specified in equation 2.

$$SOVINC_1 = SOVDEC_1 = SOV_1 \tag{2}$$

Then SOVINC and SOVDEC respectively capture positive and negative evolutions of SOV by being specified as described in equations 3 and 4:

$$
\begin{aligned}
SOVINC_t &= SOVINC_{t-1} + SOV_t - SOV_{t-1} \quad && \text{if } SOV_t - SOV_{t-1} > 0 \tag{3}\\
&= SOVINC_{t-1} && \text{otherwise}
\end{aligned}
$$

$$
\begin{aligned}
SOVDEC_t &= SOVDEC_{t-1} + SOV_t - SOV_{t-1} \quad && \text{if } SOV_t - SOV_{t-1} < 0 \tag{4}\\
&= SOVDEC_{t-1} && \text{otherwise}
\end{aligned}
$$

Thus SOVINC represents the cumulative increase of SOV over time. Similarly, SOVDEC represents the cumulative decrease of SOV over time. The next step consists of replacing the SOV series by the two sub-series SOVINC and SOVDEC in a persistent model, as specified in equation 5:

$$
\begin{bmatrix} MS_t \\ SOVINC_t \\ SOVDEC_t \end{bmatrix} = \begin{bmatrix} a_{0,MS} & \delta_{MS^t} \\ a_{0,SOVINC} & \delta_{SOVINC^t} \\ a_{0,SOVDEC} & \delta_{SOVDEC^t} \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} \beta_{11}^i & \beta_{12}^i & \beta_{13}^i \\ \beta_{21}^i & \beta_{22}^i & \beta_{23}^i \end{bmatrix} \begin{bmatrix} MS_{t-i} \\ SOVINC_{t-i} \\ SOVDEC_{t-i} \end{bmatrix}
$$

$$
+ \sum_{i=1}^{k} \begin{bmatrix} \gamma_{11}^i & \gamma_{12}^i & \gamma_{13}^i & \gamma_{14}^i \\ \gamma_{21}^i & \gamma_{22}^i & \gamma_{23}^i & \gamma_{24}^i \end{bmatrix} \begin{bmatrix} PR_{t-i} \\ REB_{t-i} \\ CPR_{t-i} \\ CREB_{t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{MS,t} \\ \varepsilon_{SOVINC,t} \\ \varepsilon_{SOVDEC,t} \end{bmatrix} \tag{5}
$$

This specification satisfies our need to disentangle the embedded effects of the increases and decreases in advertising since the impact on market share of past increases in share of voice is captured by the coefficient $\beta_{12}$, whereas the impact on market shares of past decreases in share of voice is captured by the coefficient $\beta_{13}$. These coefficients may take different absolute values. Moreover, the impulse response function (IRF) of market share (MS) due to an unexpected positive shock in SOV is computed using the coefficient $\varepsilon_{SOVINC,t}$, whereas the MS IRF due to an unexpected negative shock in SOV is computed using the coefficient $\varepsilon_{SOVDEC,t}$. Both of these coefficients may also take different absolute values. Thus, this new model specification meets our sixth requirement of asymmetric advertising response allowance.

## 3. Data and Results

We perform our analysis on several product categories: two categories from the automotive industry, and two categories from the food industry. Data consist in weekly sales volume, average price, promotion level and advertising spending between December 2003 and February 2007..
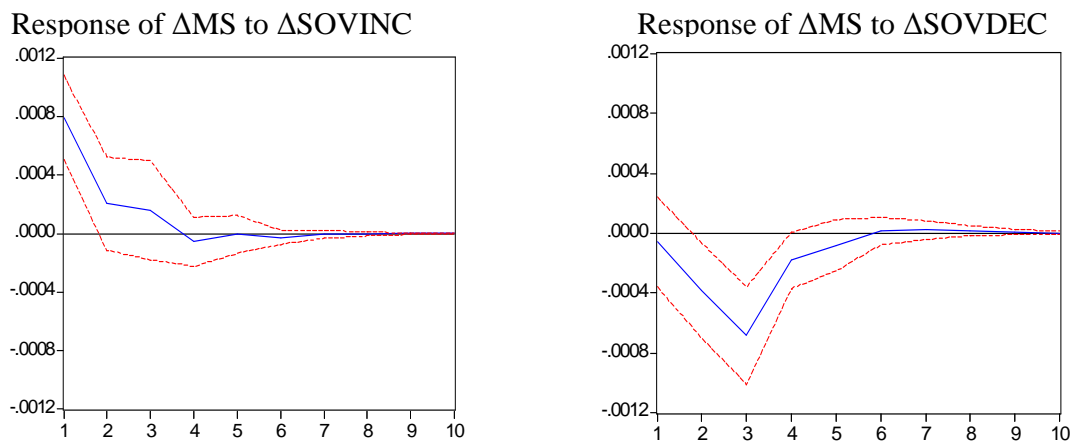
We estimate 36 models (18 benchmark VAR models and 18 asymmetric models, one for each brand), with the number of lags selected by the SBIC. We compare the results concerning goodness of fit. To compare both types of models, we use two different indicators: the Log-likelihood (LL) and the Akaike Information Criterion (AIC). Table 1 provides the indicators of model fits for all the 36 estimated models: 18 benchmark VAR and 18 asymmetric models. For each brand, both indicators LL and AIC are significantly better for the asymmetric model than for the VAR model. These results show the superiority of the asymmetric model.

### Table 1. Fit indicators of benchmark and asymmetric models

|  | Brand | Benchmark VAR Model | | Asymmetric Model | | |
|---|---|---|---|---|---|---|
|  |  | LL | AIC | LL | AIC | H1 |
| Milk Drink | A | 234.6309 | -2.968412 | 281.3738 | -3.431651 | Y |
|  | B | 394.9339 | -5.105785 | 519.1552 | -6.60207 | Y |
|  | C | 671.2028 | -8.789371 | 910.0929 | -11.81457 | Y |
|  | D | 260.9649 | -3.319531 | 345.8504 | -4.291339 | Y |
| Breakfast Bicuits | E | 501.0904 | -6.038153 | 677.2915 | -8.065327 | Y |
|  | F | 967.0014 | -11.79014 | 1268.476 | -15.3639 | Y |
|  | G | 569.1471 | -6.878359 | 672.134 | -8.001655 | Y |
|  | H | 342.1035 | -3.846641 | 407.6223 | -4.736077 | Y |
| Small Cars | CAV | 763.705 | -7.034953 | 1173.117 | -10.75582 | Y |
|  | CIV | 592.2494 | -5.417447 | 976.8192 | -8.903954 | Y |
|  | ESC | 657.6018 | -6.03398 | 1036.241 | -9.600389 | Y |
|  | NEO | 891.0876 | -8.236675 | 1366.403 | -12.57927 | Y |
|  | SEN | 701.8176 | -6.451109 | 1063.332 | -9.720117 | Y |
| Sedans | ACC | 917.1673 | -6.054999 | 1458.427 | -9.598837 | Y |
|  | MAX | 969.3029 | -6.406080 | 1457.024 | -9.589387 | Y |
|  | CEN | 1306.262 | -8.733978 | 1980.541 | -13.20367 | Y |
|  | SEB | 1330.232 | -8.836576 | 1966.292 | -13.0188 | Y |
|  | TAU | 926.0177 | -6.114597 | 1462.463 | -9.626011 | Y |

The better fit of the asymmetric model compared to the symmetric one seems to show that the advertising impact on sales is asymmetric. We illustrate this pattern with an example. Figure 2 represent the two impulse response functions (IRF's) determined by the asymmetric model. The first IRF shows that a positive unit shock in share of voice leads to a strong increase in market share that lasts only one period and that is not significant from the second period. The second IRF of the asymmetric model shows that the impact of a negative unit shock in share of voice is not symmetric to the one of a positive unit shock since this negative impact is not significant in the short term (first period) and grows in consecutive periods until the fourth one. This example is consistent with patterns found in previous research and explains why an asymmetric models leads to a better fit than a symmetric one.

**Figure 2. Impulse-Response Functions computed with symmetric and asymmetric models**



Response of $\Delta$MS to $\Delta$SOVINC



Response of $\Delta$MS to $\Delta$SOVDEC

## 4. Discussion and Limitations

Our research develops a model based on multivariate time-series analysis to capture asymmetric dynamic relationships between advertising spending and sales. We apply this model to 18 brands from four different product categories. We compare our asymmetric model to a benchmark symmetric one and show that fit indicators of the asymmetric model are better for 17 of the 18 brands from each product category. Thus, our central result is that the impact of advertising on sales is asymmetric: increases in advertising expenditure do not have a symmetric absolute impact on sales compared to decreases. This confirms the validity of the claim made by Pauwels et al. (2004a) who stated that time-series models had to capture asymmetric long term effects.

This study has some limitations. First, it is highly probable that advertising response depends on brand characteristics such as product category, position in the market or position in the life cycle. A larger dataset containing more product categories should enable inter-brand and inter-category analysis. Second, following most of time-series research, we operationalize advertising by using an indicator of share of voice based on advertising expenditure. However, recent research has shown that it is also important to account for other advertising aspects advertisement themes (Bass et al. 2007). Additional work could address the existence of an asymmetric response pattern regarding advertising quality.

# References

Aspan, M. (2009), "Payoff, for Now, from Ad Budget Cuts", *American Banker*, 174 (84), 9-10.

Bass, F.M., Bruce, N., Majumdar, S. & Murthi, B.P.S. (2007), "Wearout Effects of Different Advertising Themes: A Dynamic Bayesian Model of the Advertising-Sales Relationship", *Marketing Science*, 26 (March-April) 179-195.

Batra, R., Lehmann, D.R., Burke, J. & Pae J. (1995), "When Does Advertising Have an Impact? A Study of Tracking Data", *Journal of Advertising Research*, 35 (September), 19-32.

Dekimpe, M.G. & Hanssens, D.M. (1995), "The Persistence of Marketing Effects on Sales", *Marketing Science*, 14 (Winter), 1-21.

Dekimpe, M.G. & Hanssens, D.M. (1999), "Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability", *Journal of Marketing Research*, 36 (November), 397-412.

Kotler, P. & Caslione J.A. (2009), "How Marketers can Respond to Recession and Turbulence", *Journal of Customer Behaviour*, 8 (Summer), 187-191

Little, J. D.C. (1979), "Aggregate Advertising Models: The State of the Art", *Operations Research*, 27 (July-August), 629-667.

MacInnis, D.J., Rao, A.G. & Weiss, A.M. (2002), "Assessing When Increased Media Weight of Real-World Advertisements Help Sales", *Journal of Marketing Research*, 34 (November), 391-407.

MacLeod, C. (2009), "Global Economy and Adspend Prospects", *International Journal of Advertising*, 28 (2), 403-405.

Pauwels, K., Currim, I., Dekimpe, M., Hanssens, D.M., Mizik, N., Ghysels, E. & Naik, P. (2004a), "Modeling Marketing Dynamics by Time-Series Econometrics", *Marketing Letters*, 15 (4), 167-183.

Pauwels, K., Silva-Risso, J., Srinivasan, S. & Hanssens, D.M. (2004b), "New Products, Sales Promotions and Firm Value: The Case of the Automobile Industry", *Journal of Marketing*, 68 (October), 142-156.

Pauwels, K. & Srinivasan, S (2004), "Who Benefits from Store Brand Entry", *Marketing Science*, 23 (Summer), 364-390.

Robert, C.C. (2007), "Advertising Restrictions and Competition in the Children's Breakfast Cereal Industry", *Journal of Law and Economics*, 50 (November), 757-780.

Rust, R.T., Ambler, T., Carpenter, G.S, Kumar, V., & Srivastava, R.K. (2004), "Measuring Marketing Productivity: Current Knowledge and Future Directions", *Journal of Marketing*, 68 (October), 76-89.

Simon, H. (1982), "ADPULS: An Advertising Model with Wearout and Pulsation", *Journal of Marketing Research*, 19 (August), 352-363.

Srinivasan, S., Pauwels, K., Silva-Risso, J. & Hanssens, D.M. (2009), "Product Innovations, Advertising, and Stock Returns", *Journal of Marketing*, 73 (January), 24-43.

Thietart, R.A. & Vivas, R. (1984), "Success Strategies for Declining Activities", *International Studies of Management and Organization*, 13 (4), 77-92.

Vakratsas, D. & Ambler, T. (1999), "How Advertising Works: What Do We Really Know", *Journal of Marketing*, 63 (January), 26-43.

Vande Kamp, P.R. & Kaiser, H.M. (1999), "Irreversibility in Advertising-Demand Response Functions: An Application to Milk", *American Journal of Agricultural Economy*, 81 (May), 385-396.